



The projected impacts of climate change and fishing pressure on a tropical marine food web



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ABSTRACT

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Small-scale fisheries, especially those from developing countries, are vital for millions. Understanding the impact of environmental and human factors on fish stocks and yields and how they might change is crucial to ensure the sustainable use of aquatic resources. We developed an ecosystem model using Ecopath and Ecosim (EWE) to investigate changes in target species biomass and ecosystem attributes over 83 years (2017–2100) caused by different scenarios of fishing pressure and ocean warming in the Brazilian Northeastern continental shelf. The simulations considered three IPCC climate change scenarios (RCP2.6 [0.42 °C], RCP4.5 [1.53 °C], and RCP8.5 [4.02 °C]) and four fishing pressure scenarios: two with increased pressure (10% and 30%) and two with decreased pressure (−10% and −30%). The Ecopath model indicated that the Brazilian Northeastern continental shelf ecosystem is a grazing-based system with high biomass in macroalgae and detritus compartments, supporting a diverse community of consumers. Our simulations projected overall reductions in the biomass of target species, mainly under extreme climate change. Increasing temperatures and fishing efforts reduced the biomass of large predatory species and the food web length in several scenarios. Although projected changes in ecological network and information metrics were of lower magnitude, results predicted declines in production/respiration ratio, material cycling, and ascendency (variable related to trophic specialization, internalization, and material cycling) with climate change. These declines were likely linked to increased respiration rates, metabolic costs, and lower trophic efficiency with elevated temperatures. Together, our results show how climate change and fishing pressure can change the structure of coastal ecosystems, potentially leading to undesirable alternative states for fisheries. Our approach demonstrates the effectiveness of ecosystem-based modeling in projecting likely trajectories of change, which can be especially useful for resource management in data-limited conditions.

1. Introduction

Global human-induced climate change, combined with other anthropogenic effects such as overfishing and environmental

degradation, can dramatically impact the structure and functioning of marine food webs (Ani and Robson, 2021; Bartley et al., 2019; Bieg and McCann, 2020; Kortsch et al., 2015). These changes can greatly affect marine fisheries' production and potential catches of historically

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exploited species, with implications for food security and ecosystem services (Bentley et al., 2020; Stoeckl et al., 2017).

Temperature is a crucial factor affecting organisms' life cycle and can directly influence ecosystems (Free et al., 2019; O'Connor et al., 2007). Classical temperature-size rule (TSR) predictions suggest ectotherms' asymptotic body size declines as organisms grow faster and mature earlier at warmer temperatures (Atkinson, 1994). In addition, smaller fish species tend to perform better in warm, oxygen-depleted waters than larger species, suggesting they may become more abundant relative to their larger counterparts as climate change progresses (Pauly, 2021; Rubalcaba et al., 2020; Salvatucci et al., 2022). Climate change may shorten food webs (i.e., reduce the number of trophic levels) by increasing metabolic costs, reducing energy flow efficiency, and limiting the energy available for top predators (Barneche et al., 2021). Nonetheless, warming waters can affect species' productivity and distribution at global scales via direct (e.g., increasing metabolism rates) or indirect processes (e.g., water stratification, oxygen supply, and acidification) (Baumann, 2019; Doney et al., 2009; Garcia-Soto et al., 2021; Pecl et al., 2017). Previous studies indicate species distributions are already moving toward higher latitudes and deeper areas to track optimum temperature ranges (Pinsky et al., 2020). Ultimately, species may not adapt to the new environmental conditions, and ecosystems may undergo irreversible changes (Pecl et al., 2017).

A primary concern is how climate change will affect the yield of commercial and small-scale fisheries (Bahri et al., 2018; Hoegh-Guldberg and Bruno, 2010; Young et al., 2012). Fish protein is essential for food security for over 2.9 billion people (FAO, 2023). In addition, small-scale fisheries employ 40 million people worldwide and supply nearly 80% of the fishery production of several countries (FAO, 2023). In many regions worldwide, fishing stocks have already been dangerously depleted due to overfishing, and fish communities have lost large, highly-valued top predators that are more sensitive to fisheries due to a series of life-history traits, such as slow growth and late-maturity (Pauly et al., 1998; Winemiller, 2005).

The northeastern coast is the longest of the Brazilian coastal regions and supports a high aquatic biodiversity with substantial fish landings volume ($\approx 186,000$ metric tons per year; MPA, 2011). Small-scale fisheries are responsible for most of this production (Lucena-Frédu et al., 2021). The region is home to about 675,000 coastal fishers, more than half of the country's total, with high participation of women (>50%) (MPA, 2024). These fisheries directly employ around 200,000 people, with an estimated ratio of one job at sea to four on land (Bevilacqua et al., 2019). However, of the 135 marine fish stocks analyzed, only 49% have their status assessed. Of those, 67% are overfished, and 27% are in the process of overfishing (Oceana, 2022). The lack of data on fish stocks presents a significant challenge for maintaining the sustainability of fisheries, which are crucial for traditional fishing communities that rely on them for both income and food security. As in other developing countries, a large portion of Brazil's coastal population depends on fish for subsistence, making them highly vulnerable to changes in fish stocks that are poorly monitored and managed. This data deficiency, particularly in small-scale fisheries, hampers effective management and conservation efforts, increasing the risk of local and regional fishery collapses, as seen in other areas globally (Allison et al., 2009; Costello et al., 2016; Dowling et al., 2015; Gaines et al., 2018; Le Bris et al., 2018; McClenahan et al., 2016; Putten, 2021).

Analyzing the main issues of the fishing sector requires a holistic approach that integrates environmental, social, and economic features (Link and Browman, 2017; Long et al., 2015). Marine Ecosystem Models (MEMs) provide an integrated understanding of the ecosystem and economic dynamics (Steenbeek et al., 2021) since they can incorporate the impacts of multiple anthropogenic and environmental stressors (Coll et al., 2020; Boyce et al., 2020), and fisheries scenarios (Corrales et al., 2017; Serpetti et al., 2017) to quantify ecosystem changes and the effectiveness of proposed management actions at local, regional, and global scales (Boyce et al., 2020; Christensen et al., 2015; Coll et al.,

2016). Despite the urgent need to improve fisheries management, the application of MEMs to simulate fisheries' impact and environmental change scenarios in Brazil still needs to be explored (but see Bornatowski et al., 2017; Freire, 2005; Lira et al., 2021a).

Here, we used a regional MEM to investigate the potential future effects of ocean warming and increasing fishing efforts on the food web of the Brazilian Northeastern continental shelf. We hypothesize that higher fishing pressure and warmer temperatures lead to lower fish biomass, particularly of large species at higher trophic positions, shortening the food web and increasing turnover rates. Since the region lacks a consistent monitoring program, we tested the sensitivity of our conclusion to the inherent uncertainty of the input parameters (e.g., biomass estimates) and the assumptions about the food web control (e.g., top-down vs. bottom-up control; Angelini et al., 2013).

2. Methods

2.1. The Brazilian Northeastern coast

We developed a MEM for the Brazilian Northeastern coast ecosystem using the Ecopath with Ecosim (EwE) software (version 6.6.5, available at www.ecopath.org; Christensen and Walters, 2004; Heymans et al., 2016). The modeled area ($31,105 \text{ km}^2$) covers the Northeastern Brazilian continental shelf between the states of Rio Grande do Norte ($5^\circ 0' \text{S}$; $35^\circ 0' \text{W}$) and Alagoas ($10^\circ 0' \text{S}$; $36^\circ 0' \text{W}$) (Fig. 1). It coincides with the central area of surveys from the ABRACOS Project (Acoustic along the Brazilian Coast) (Bertrand, 2015, 2017) that provided the observations to parameterize the model's biomass values and most diet composition information. The continental shelf varies considerably in shape and width, with an average width of 40 km and a depth of 40–80 m (Meirelles et al., 2017; Vital et al., 2010). The marine ecosystem is oligotrophic, with water temperatures between 25.5° and 29.6°C (Eduardo et al., 2018; Farias et al., 2022) and is characterized by extensive reefs lined with many broad sandy beaches (Mayal et al., 2009). River sedimentation load is low because the rivers are short and intermittent (Vital et al., 2010).

2.2. The Ecopath baseline model

Ecopath models rely on linear equations incorporating production and consumption, quantifying energy flow between species and functional groups with the diet composition matrix. These equations are founded on the mass balance principle within ecosystems, ensuring equilibrium. The master equation of Ecopath is:

$$B_i \times \left(\frac{P}{B}\right)_i \times EE_i - \sum_{j=1}^n \left(B_j \times \left(\frac{Q}{B}\right)_j \times DC_{ij} \right) - EX_i - Y_i = 0 \quad \text{Equation 1}$$

where B_i is the biomass of functional group i (herein, group i); P/B_i is the Production/Biomass rate of group i , which is equal to its total mortality Z (Allen, 1971); EE_i is the Ecotropic Efficiency of group i , which varies from 0 to 1 and represents the fraction of the production of the group that is used within the system or exported from the system. The multiplication of these three terms defines the growth of the group i . This growth is balanced by the consumption of group j , which is estimated by the sum of the biomass of the predator j (B_j) plus the respective consumption rate (Q/B_j) per unit of biomass of predator j ; DC_{ji} is the fraction of group i in the diet of consumer j . Besides their consumption, the growth of group i is also balanced by EX_i , which is its export (migration to other ecosystems, in this case, zero), and Y_i , which is its biomass caught (yield) through fishing.

Our baseline model quantified the energy flow among 55 components: 36 fish species or functional groups (species that share similar prey and predators), ten invertebrates (e.g., zooplankton, corals, cephalopods, lobsters, shrimps, crabs, jellyfish), three mammals (dolphins, whales, and manatee), one seabird, one reptile (Cheloniidae), three

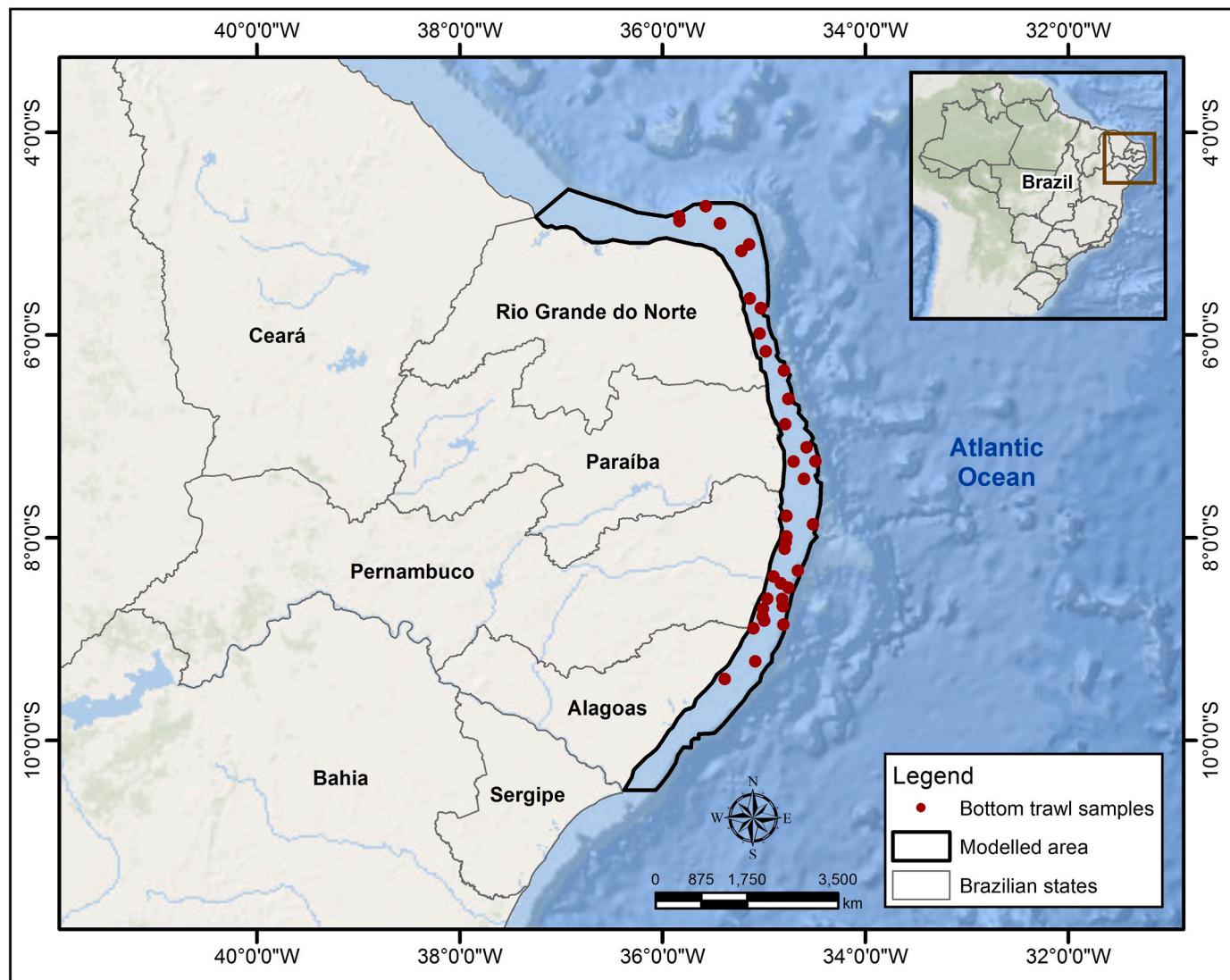


Fig. 1. A map of the Brazilian Northeastern coast shows the modeled area between the Rio Grande do Norte and Alagoas states. Red circles represent the bottom trawl samples of the ABRACOS project, which subsided the biomass values of the model (Bertrand, 2015, 2017). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

primary producers (phytoplankton, macroalgae, and seagrasses), and one detritus (Appendix A, Table A1). Details about input parameters, model structure, and statistical analyses are provided below.

2.2.1. Biomass data

Biomass estimates were derived from sampling carried out in August–September 2015 and April–May 2017 aboard the French R/V ANTEA (Bertrand, 2015, 2017). A bottom trawl net (body mesh: 40 mm, cod-end mesh: 25 mm, entrance dimensions horizontal × vertical: 28 × 10 m) was deployed to collect data (Eduardo et al., 2020). Biomass values for 29 groups of fishes were estimated using the weight (TW) of each species caught divided by the total estimated area (trawl distance × the average net area opening; for a detailed explanation, see Eduardo et al., 2018). The remaining seven functional groups of fish had their biomass value estimated by the Ecopath model. Estimates of the biomass values of spiny lobster and squids were also obtained under the ABRACOS project. Biomass values were estimated as grams/m⁻², accounting for species caught with specific bottom trawl nets. For crabs, shrimps, manatees, seabirds, invertebrates, and others, the biomass values were obtained from the literature for the region (Alves et al., 2013; Freire, 2005; Freire et al., 2008). For more details, see Appendix A (Table A1)

and Appendix B (Table B1).

2.2.2. Species traits

To analyze the ecosystem structure, taxa were categorized according to their risk of extinction, fishing use, and taxonomy (Appendix A, Table A1). Specifically, we used the IUCN (International Union for Conservation of Nature) Red List to divide taxa into seven threatened categories: Not Evaluated, Data Deficient, Least Concern, Near Threatened, Vulnerable, Endangered, and Critically Endangered (IUCN, 2024). Fishes were classified as either target or non-target species by fisheries, as indicated in fisheries reports (e.g., IBAMA, 2007; IBGE, 1989). We also divided consumers into three main groups: i) fishes, ii) invertebrates, and iii) mammals, birds, and reptiles (sea turtles). Although mammals, birds, and sea turtles belong to different functional groups, we grouped them because they are often considered charismatic and hold significant value for conservation biologists and the public (Albert et al., 2018). Additionally, we estimated the maximum length of each fish taxa using data available on FishBase (Froese and Pauly, 2024). The maximum length was then converted to maximum biomass (g) using the Bayesian hierarchical approach proposed by Froese et al. (2014). For more details, see Appendix A, Table A1.

2.2.3. Metabolic parameters and trophic information

The Production/Biomass (P/B) rate measures how quickly new biomass is produced compared to the existing biomass and is considered equivalent to total mortality (Z) (Allen, 1971). The equivalence between P/B and Z has been assumed across the literature as the production of new biomass must balance the loss of biomass in stable ecosystems (Christensen and Walters, 2024). We estimated P/B for fish species using Pauly (1980), while for other compartments, we sourced it from the literature (Araújo et al., 2017; Coll et al., 2006; Freire, 2005; Freire et al., 2008; Illescas, 2012; Lira et al., 2018; Nascimento et al., 2012; Wolff et al., 2000).

Likewise, the Consumption/Biomass (Q/B) rate, i.e., the amount of food required by the organism relative to its weight, was obtained either from two previous studies (García and Duarte, 2002; Giarrizzo et al., 2013) or estimated by empirical regression (Palomares and Pauly, 1998).

The diets (Appendix A, Table A2) were established using local and recent data from the ABRACOS Project (Bertrand, 2015, 2017) and also local information already published (Freire et al., 2008; Lira et al., 2021b; Soares et al., 2020; Vaske Júnior et al., 2009; Appendix B, Table B2).

2.2.4. Fisheries data

We considered several official fisheries reports (e.g., IBAMA, 2007; IBGE, 1989) and relevant literature (Freire et al., 2021). We estimated the catch values for 2017 (model reference year) by calculating the mean of reported catches from 2014 to 2015, as provided in the Supplementary Material of Freire et al. (2021). We adjusted these values using the biomass estimates for each species/group (as described above). The landings within our modeled area are divided into two sectors: artisanal and industrial, with artisanal fisheries representing nearly 90% of the total catch. Given the relevance of artisanal fisheries in this sector to represent commercial fishing in the region, we focused solely on artisanal data, adopting the same categorization for small-scale fisheries. We then divided the landing values by the modeled area (31,105 km²).

2.2.5. Ecopath diagnostics and parameter uncertainty

To evaluate the ecological plausibility of the Ecopath (baseline) model, we used the pre-balance diagnostics (Prebal; Link, 2010), which assesses whether Ecopath input parameters adhere to the general eco-physiological characteristics of marine ecosystems. We also used the Pedigree index (Christensen et al., 2005) to attribute the degree of uncertainty to each parameter input data (see section 2.3.2; and Appendix A, Table A3).

2.2.6. Main outputs

We utilized the Lindeman spine diagram to evaluate the overall structure of our Ecopath models. This diagram encapsulates the exchanges among various trophic levels and the detritus compartment, aiding in visualizing the energy flow within the system (Christensen et al., 2005). A detritivory to herbivory ratio was calculated to identify the main flow path that supports the food web of the Brazilian Northeastern coast region.

Additionally, we conducted a Mixed Trophic Impact (MTI) analysis to reveal both the direct (trophic link) and indirect (trophic cascade) impacts of single species or functional groups on others (Christensen and Walters, 2004; Gamito and Erzini, 2005; Mavuti et al., 1996). MTI values vary from -1, when the impact is negative, to 1, when the impact is positive. MTI values were then used to calculate the keystone species index (#3KSi), which indicates species with a disproportionate effect on the trophic network relative to their biomass (Valls et al., 2015).

2.3. Temporal dynamics and simulations

We used Ecosim to model the temporal dynamics and simulate the

impact of climate change and fishing on ecosystem structure and properties. In addition to the mass-balanced Ecopath parameters, Ecosim considers other parameters related to behavior and temporal dynamics that allow the dynamic simulation of changes in biomass over time, as follows:

$$\frac{dB_i}{dt} = g_i \sum_{j=1}^n Q_{ij} - \sum_{j=1}^n Q_{ji} + I_i - (M_{0i} + F_i + e_i) \times B_i \quad \text{Equation 2}$$

where $\frac{dB_i}{dt}$ represents the change in the biomass of functional group i (herein, group i) (B_i) over time dt ; g_i is the gross growth efficiency of group i (P/Q ratio); Q_{ij} and Q_{ji} , represent consumption by group i on j and by j on i , respectively. I_i is the immigration of group i ; M_{0i} is the non-predation rate of natural mortality of group i ; F_i is the fishing mortality of group i ; and e_i is the emigration of the group i . Estimations of consumption rates (Q) are calculated based on the concept of the foraging arena, which expresses that through predator behavior, at any time, only a fraction of a total prey biomass is vulnerable to predation (Ahrens et al., 2012; Walters et al., 1997).

The consumption rate is defined as:

$$Q_{ij} = \frac{a_{ij} \times v_{ij} \times B_i \times P_j \times T_j \times M_{ij} / D_j}{v_{ij} + (v_{ij} \times T_i \times M_{ij}) + (a_{ij} \times M_{ij} P_i \times T_j / D_j)} \times f(Env_{function}, t) \quad \text{Equation 3}$$

where a_{ij} is the rate of effective search for prey i by predator j , v_{ij} is the vulnerability parameter, T_i represents prey i relative feeding time, T_j is the predator j relative feeding time, B_i is prey i biomass, P_j is the predator j biomass, M_{ij} is the mediation forcing effects, and D_j represents effects of handling time as a limit to consumption rate. Environmental response functions ($Env_{function}, t$) represent the tolerance of a species/group to an environmental driver, here temperature. With respect to all the parameters above, we only modified vulnerability and environmental response (see below). The following parameters remained unchanged throughout the simulation (default values): rate of effective search (time spent foraging), relative feeding time (time that a predator spends feeding), mediation forcing effects (indirect factors that influence predator-prey interactions), and handling time (the limited time required for a predator to capture, subdue, and consume its prey). Below, we described the simulation scenarios, model parameters, and assumptions.

2.3.1. Vulnerabilities settings

Vulnerability parameters (v_{ij}) are grounded in the foraging arena theory and determine the extent to which each prey is susceptible to predation, constituting an essential component in the temporal dynamics model (Walters et al., 1997). Because reliable time-series data to calibrate the model were unavailable, we followed the approach used by Rehren et al. (2022). Specifically, we tested the sensitivity of our results to four different assumptions about the functioning of the food web: v1) Vulnerability value equals 1 to simulate an ecosystem with predators close to their carrying capacity and that is controlled predominantly by bottom-up process; v2) Vulnerability value equals 2 to simulate a system that is more distant from the carrying capacity and is controlled similarly by top-down and bottom-up processes (mixing control); v7) Vulnerability value equals 7 to simulate a system far from the carrying capacity that is top-down controlled; and vTL) Vulnerability value increases with trophic level (Appendix A, Table A4), as expected when the system is already experiencing fishing down the food web (i.e., species from higher trophic levels exhibit a greater distance from carrying capacity compared to species from lower trophic levels due to higher fishing mortality rates) (Christensen, 1996). We assessed the impacts of temperature increase and changes in fishing efforts for each vulnerability approach, running several forecast scenarios between 2017 and 2100.

2.3.2. Parameter uncertainty

We assigned “Pedigree values” to the key input parameters of our model, specifically B, P/Q, Q/B, Diet, and catch (see Table A3). Pedigree values range from 0, indicating low data quality, to 1, representing high data quality. High-quality data are characterized by local and precise sampling, while low-quality data are derived from literature and models of other systems. As data quality increases, the uncertainty associated with each parameter, measured by the coefficient of variation (CV), decreases. The assignment of Pedigree values and their corresponding CVs followed the default options established by Ecopath (Christensen et al., 2005).

To explore the influence of these Pedigree values on Ecopath input parameters during our simulations, we implemented a Monte Carlo uncertainty routine with 100 permutations (Christensen and Walters, 2004; Heymans et al., 2016). In each iteration, input parameters were determined through random sampling from their respective distributions (Gaussian); the mean of the distribution was based on the initial values provided in the static model, and the standard deviation was derived from the assigned Pedigree values. This approach generated 100 variations of the model, each with slightly different input parameters, enabling us to statistically assess the consistency of the output parameters (e.g., biomass, ecosystem indicators – see section 2.3.4).

2.3.3. Future scenarios

We obtained temperature projections for Representative Pathway Concentration (RCP) scenarios from the World Meteorological Organization Climate Explorer (WMO, 2020) using the Coupled Model Inter-comparison Project (CMIP5). The RCPs represent radiative forcing trajectories based on four “marker” scenarios from the IPCC AR5 database, which contains over 1100 emissions IPCC, 2014 scenarios (IPCC, 2014). We utilized three scenarios for our climate simulations, ranging from mild to worst-case: 1) RCP2.6, which represents a low-emission pathway with radiative forcing of 2.6 W/m² by 2100; 2) RCP4.5, a plausible intermediate scenario with radiative forcing of 4.5 W/m² by 2100; and 3) RCP8.5, a less likely but more extreme scenario with radiative forcing of 8.5 W/m² by 2100 (Burgess et al., 2023). We opted to model the unlikely RCP8.5 extreme scenario as it has the potential to motivate action, strengthen resilience, and shape policy decisions, particularly in emergency response (Kemp et al., 2022).

According to global scenarios, by 2100, surface temperatures in the Brazilian Northeastern region are projected to increase from 0.3 to 1.7 °C under the RCP2.6 scenario, 1.1–2.6 °C under RCP4.5, and 2.6–4.8 °C under RCP8.5 (IPCC, 2014). For our simulations, we used only the mean of these projected temperatures (RCP2.6: 0.42 °C, RCP4.5: 1.53 °C, RCP8.5: 4.02 °C). We tested these three scenarios considering fishes’ preferable and survivable temperature ranges (trapezoidal response functions) as environmental response functions (Serpetti et al., 2017). These thermal ranges were obtained from AquaMaps (Appendix A, Fig. A1) (Kaschner et al., 2019), and they are used to adjust the foraging arena size of the functional groups in the model, with maximum feeding occurring at ideal temperatures and declining rates as temperature departs from it (Christensen et al., 2014). The species response curve in Aquamaps takes on a trapezoidal shape, which is consistently highest when environmental conditions align with its preferred parameter range (from MinP to MaxP). When conditions fall outside this range, the response decreases linearly until it reaches the species’ absolute minimum or maximum thresholds (MinA or MaxA), considered zero beyond these threshold limits. Thus, the biomass of functional groups outside their preferred temperature ranges tends to decline due to lower consumption rates. We note that temperature response functions were applied only to fish functional groups, meaning that non-fish groups are indirectly affected by climate change as they respond to changes in the biomass and consumption of impacted fish species.

We also defined hypothetical trends in fishing efforts according to observed values from a small-scale fishery perspective (Bevilacqua et al.,

2016). We systematically adjusted the fishing effort by incrementally increasing or decreasing it by 10% and 30% for each fishing gear. Essentially, we applied a linear increase or decrease in fishing pressure until reaching the target value (e.g., -30%) in the final year of simulation (2100).

Summarizing, for each vulnerability value (Table 1), we simulated the four fishing effort scenarios maintaining the temperature constant, which generated a total of 16 scenarios (e.g., V1_Eff10%: vulnerability value = 1 and effort = 10%, temperature constant; V7_Eff-30%, vulnerability value = 7 and decreasing effort = 30%, temperature constant; and so on). Moreover, for each vulnerability value, we simulated the three temperature scenarios (Table 1), maintaining the fishing effort referent to the baseline model (e.g., V2_RCP4.5: vulnerability value = 2 [mixing control]; RCP4.5 [1.53 °C] and fishing effort constant; VTL_RCP8.5: vulnerability value depending on Trophic Level of the component; RCP8.5 [4.02 °C] and fishing effort constant) (see Appendix A, Table A1 for details). To verify if the temporal trends were not a byproduct of the vulnerability values chosen, we also conducted simulations for each vulnerability value without considering any climate or fishing pressure scenario (Table 1) as control scenarios.

2.3.4. Ecosystem indicators

We calculated 16 leading ecosystem indicators to assess the food web status (Table 2): Total Biomass (B), Production/Biomass (P/B), Net Production (Net P), Production/Respiration (P/R), Biomass/Throughput (B/T), Finn Cycling Index (FCI), Ascendency, Average Trophic Level (TL), the total biomass of endangered species, Mean Weight (MW) of fish species, the total biomass of invertebrates, total biomass of mammals/birds/reptile species, total biomass of phytoplankton, total biomass of detritus, total biomass of multicellular producers, and total catch. These indicators were chosen given their importance in understanding ecosystem functioning and development (Christensen and Pauly, 1998; Keppeler et al., 2024), the “fishing-down food web” hypothesis (Pauly et al., 1998), and species conservation (IUCN, 2024) (Table 2). All these indicators were estimated using the EcoIND plug-in (Coll and Steenbeek, 2017) built into the EwE software. The only exception was the Mean Weight (MW) of fish species, which was calculated using the community-weighted mean (CWM) approach in the R package BAT (Cardoso et al., 2023; R Core Team, 2024). It is important to note that EwE is not an individual-based model; therefore, our metric (i.e., MW of fish species) reflects interspecific differences in body size and the total biomass of each fish species or fish functional groups.

2.3.5. Temporal trends consistency

We tested the consistency of the temporal trends using the 100 simulations generated by the Monte Carlo approach. Specifically, we calculated the change ratio of taxa biomasses and ecosystem indicators by dividing their final condition in 2100 by their initial condition in 2017 for each simulation. Then, we calculated the 90% confidence interval (CI) for each scenario. Temporal trends were divided into three main categories: i) Neutral, when CI encompassed 1; ii) Positive, when

Table 1

Variables to compose the scenarios simulations. For each vulnerability value, we simulated i) the four fishing effort scenarios maintaining the temperature constant, and ii) the climate scenarios maintaining the fishing effort constant. In addition, we simulate the food web dynamics for each vulnerability value without adding any climate or fishing effort scenario. See Table S1 for more details.

Vulnerabilities values trophic control	Fishing Effort (relative to baseline)	Temperature Scenarios (RCP from IPCC)
1 - bottom-up	10%	2.6 (0.42 °C)
2 – mixing	30%	4.5 (1.53 °C)
7 - top-down	-10%	8.5 (4.02 °C)
TL - trophic level	-30%	

Table 2

Ecosystem indicators used to assess the effect of climate change and fishing effort on the Brazilian Northeastern coast ecosystem.

Indicator	Ecological interpretation	Reference
Total Biomass (B)	The quantity of standing biomass	Odum (1969)
Production/Biomass (P/B)	Biomass growth (turnover biomass rate)	Odum (1969)
Net Production (Net P)	Accumulation of living organic matter	Odum (1969)
Production/Respiration (P/R)	The relationship between the energy captured and the expenditure on maintenance	Odum (1969)
Biomass/Throughput (B/T)	The amount of standing biomass sustained by the energy flow	Odum (1969)
Finn Cycling Index (FCI)	The proportion of an ecosystem's throughput that is recycled	Finn (1976)
Ascendency	A measure concerning the scale and level of organization within an ecosystem, encompassing both its structural and functional aspects, including network topology and the transfer of energy and matter among species. Ascendency is positively associated with various ecosystem characteristics outlined in Odum's theory of ecosystem development, such as speciation, trophic specialization, internalization, and cycling. Generally, ecosystems with higher ascendency exhibit (1) a greater proportion of energy flows concentrated in specialized pathways and (2) a higher optimization of energy use and overall maturity.	Ulanowicz (2000)
Mean Trophic Level (MTL)	Mean trophic level across all species of a given community. It is often used to test predictions of the fishing-down food web hypothesis.	Pauly et al. (1998)
Total biomass of endangered species	Measures the abundance of endangered species (by IUCN) in the community. The higher the metric, the lower the risk of extinction.	
Mean Weight (MW) of fish species	Mean body size of fish species in the community. It is used to test predictions of the fishing-down food web hypothesis.	Pauly et al. (1998)
Total Catch	Total biomass of target species captured by fishers. This is a good indicator of fishing production	
Total biomass of invertebrates	The combined biomass of invertebrates, including crustaceans, mollusks and zooplankton.	
Total biomass of mammals, birds, and reptiles	The combined biomass of mammals, birds, and reptiles.	

CI was higher than 1; and iii) Negative, when CI was lower than 1.

3. Results

3.1. The Ecopath baseline model

The Pre-balance diagnostics (Prebal) confirmed that the model was robust and realistic with P/B and Q/B values negatively correlated to Trophic Levels (Appendix A, Fig. A2). The model showed remarkably high biomass in basal compartments, including detritus and macroalgae (Table 3, Fig. 2). The leading top predators were Sharks (*Carcharhinus* spp., *Sphyrna* spp.) (TL = 4.34), *Scomberomorus* spp. (TL = 4.33), and Other Piscivores (e.g., *Synodus* spp., *Aulostomus* spp., *Sphyraena* spp.) (TL = 4.12). As expected, large mammals exhibited the lowest P/B and Q/B rates.

The primary production of the Brazilian Northeastern model primarily originated from macroalgae, with contributions from seagrass and phytoplankton. The primary production/respiration rate was close

to 1 (P/R = 1.64), and catches added up to 0.189 t/km⁻² per year for 19 species or groups of fish. The mean trophic level of the catch was 3.50. The Herbivory: Detritivore rate approximated 5, showing that the ecosystem is grazing-based with a high Finn cycling index of 21.6%.

Other Piscivores, Sciaenidae, and *Acanthostrocion* spp. were the main fish groups that negatively impacted the largest number of groups in the system (Fig. 3). Producers' groups, in general, had a stronger positive impact. Sharks, the top predator, were identified as the main keystone functional groups, followed by Clupeiformes (*Chirocentrodon bleekeri-anus*, *Lycengraulis grossidens*), Manatee, *Acanthostracion* spp., Other Piscivores, *Scomberomorus* spp., Squids, and *Micropogonias furnieri* (Appendix A, Table A5).

3.2. Simulation scenarios on biomass target groups

The overall biomass of target species declined up to 37% under the most intense climate scenario (RCP8.5), whereas the impact associated with RCP2.6 and RCP4.5 was of lesser magnitude and similar (up to 11%; Fig. 4). The scale of biomass changes ultimately depended on the food web control type (vulnerability parameters). Under the bottom-up (v1) assumption, species biomass had a neutral response to climate change in all scenarios. Predictions of a model with mixing control (v2) suggested declines for 68% of the target species in the RCP8.5 scenario and 21% and 16% in the RCP4.5 and RCP2.6 scenarios, respectively. Increases in biomass were only observed in the RCP4.5 and RCP2.6 scenarios (38% of the target species in both cases). Models dominated by top-down control (v7) had ~42% of the target species with negative responses in the RCP8.5 scenario. This number was reduced to ~11% and 16% in the RCP4.5 and RCP2.6 scenarios, where neutral responses dominated (~84% and ~74% of the target species). Negative responses were less common and restricted to the RCP4.5 and RCP2.6 scenarios (5% and 11% of the target species, respectively). In models assuming vulnerability changes with species' trophic level (vTL), the results were similar, with most target species declining in the RCP8.5 scenario (~49%) and higher dominance of neutral responses in the RCP4.5 and RCP2.6 scenarios (~68% and ~63% of the target species, respectively). One target species with positive association (5%) was observed in the RCP8.5 scenario, whereas this number increased to 3 (16%) and four target species (21%) in the RCP4.5 and RCP2.6 scenarios, respectively. *Hypanus* spp. and *Acanthostracion* spp. were among the most negatively impacted taxa by climate change (Fig. 5; Appendix A, Table A6). Conversely, *Lutjanus* spp. and Other Piscivores were among the most benefited.

Fishing pressure had a limited impact (<5%) on the overall biomass of target species (Fig. 4). Declining trends in target species biomass were mainly observed in the scenario of a 30% increase in fishing pressure (v1: 84%, v2: 32%, v7: 16%, vTL: 16% of the target species) where positive trends were more associated with a 30% decline in fishing pressure (v1: 84%, v2: 37%, v7: 5%, vTL: 5% of the target species). Neutral temporal trends dominated scenarios of a 10% increase (v1: 74%, v2: 79%, v7: 100%, vTL: 100% of the target species) and a 10% decrease in fishing pressure (v1: 68%, v2: 100%, v7: 100%, vTL: 100% of the target species) (Fig. 4). Sharks, *Epinephelus* spp., and *Caranx* spp. were the most sensitive to fishing pressure, particularly in scenarios of a 30% fishing pressure increase (Fig. 5; Appendix A, Table A6). Sharks were the most benefited group in scenarios of a 30% fishing pressure decline. No species consistently benefited in scenarios of a 10% decline in fishing pressure.

Temporal trends in target species biomass derived from baseline models, which do not consider temperature or fishing pressure changes, were neutral for all food web assumptions (v1, v2, v7, and vTL; Appendix A, Table A6).

3.3. Ecological indicators

The initial values estimated by Ecopath for the ecological indicators

Table 3

Parameters values for the groups in the Brazilian Northeastern Ecopath model. TL: Trophic Level; B: biomass; P/B: production/biomass; Q/B: consumption/biomass; EE: Ecotrophic Efficiency. Bold values were calculated by Ecopath. For details about the species composition within each functional group, see [Appendix A, Table A1](#). For references, see [Appendix B, Tables B1, B2, B3, and B4](#).

No.	Group name	Description	TL	B (t/km ²)	P/B (year ⁻¹)	Q/B (year ⁻¹)	EE	Catches (t/km ² /year)
1	<i>Holocentrus adscensionis</i>	Fish	3.28	0.374	1.57	10.00	0.89	0.001
2	<i>Pseudupeneus maculatus</i>	Fish	3.35	0.668	0.82	10.80	0.97	0.001
3	<i>Pomacanthus paru</i>	Fish	2.49	0.360	0.72	16.00	0.32	
4	<i>Opisthonema oglinum</i>	Fish	3.14	0.080	2.11	16.86	0.81	
5	<i>Chloroscombrus chrysurus</i>	Fish	3.19	0.057	4.41	12.45	0.47	
6	<i>Fistularia tabacaria</i>	Fish	3.69	0.050	1.57	9.22	0.67	
7	<i>Alphistes afer</i>	Fish	3.31	0.021	0.64	3.00	0.53	
8	<i>Dactylopterus volitans</i>	Fish	3.25	0.026	0.48	6.51	0.90	
9	<i>Ocyurus chrysurus</i>	Fish	3.39	0.048	0.50	7.90	0.98	0.008
10	<i>Micropogonias furnieri</i>	Fish	3.51	0.058	2.00	5.10	0.90	0.002
11	<i>Trichiurus lepturus</i>	Fish	3.83	0.269	0.23	1.14	0.80	
12	<i>Haemulon</i> spp	Fish	3.29	2.818	2.25	5.60	0.42	0.004
13	<i>Hypanus</i> spp	Fish	3.71	0.839	0.60	2.65	0.89	0.004
14	<i>Acanthurus</i> spp	Fish	2.12	0.660	1.22	9.00	0.07	
15	<i>Lutjanus</i> spp	Fish	3.65	0.425	0.33	2.90	0.26	0.022
16	<i>Acanthostracion</i> spp	Fish	2.77	0.316	0.44	10.57	0.76	
17	<i>Monacanthus</i> spp	Fish	2.30	0.020	0.44	10.57	0.25	
18	<i>Scomberomorus</i> spp	Fish	4.33	0.042	1.08	4.45	0.80	0.027
19	<i>Caranx</i> spp	Fish	4.08	0.029	0.50	1.00	0.97	0.014
20	<i>Epinephelus</i> spp	Fish	4.10	0.003	2.29	5.30	0.90	0.006
21	<i>Sparisoma</i> spp	Fish	2.22	0.046	1.55	7.13	0.14	0.001
22	<i>Mugil</i> spp	Fish	2.04	0.350	4.00	22.60	0.80	0.028
23	<i>Cynoscion</i> spp	Fish	3.67	0.331	2.00	5.70	0.80	0.014
24	Gerreidae	Fish	3.11	0.100	1.33	6.00	0.80	0.009
25	Sciaenidae	Fish	3.49	0.900	0.64	3.00	0.99	
26	Ariidae	Fish	3.67	0.099	0.90	4.00	0.80	0.005
27	Haemulidae	Fish	3.28	0.180	2.00	4.00	0.98	0.004
28	Pleuronectiformes	Fish	3.55	0.150	0.26	2.02	0.98	
29	Clupeiformes	Fish	3.39	0.090	1.40	6.00	0.99	
30	Puffer	Fish	3.09	0.616	3.17	11.00	0.80	
31	Sharks	Fish	4.34	0.078	0.33	1.87	0.60	0.015
32	Other Piscivores	Fish	4.12	0.700	1.25	3.20	0.99	0.006
33	Other Omnivores	Fish	3.22	0.382	2.00	10.57	0.94	
34	Other Zoobenthivores	Fish	3.35	1.050	0.37	6.34	0.98	0.005
35	Other Herbivores	Fish	2.35	0.096	2.00	20.00	0.68	
36	Other Invertivores	Fish	3.00	0.350	1.44	10.57	0.30	0.013
37	Jellyfish	Invertebrate	3.32	0.048	28.51	50.48	0.99	
38	Crabs	Invertebrate	2.13	2.000	5.23	10.82	0.79	
39	Shrimps	Invertebrate	2.21	3.010	7.75	26.00	0.51	0.096
40	Lobster	Invertebrate	2.56	1.970	1.28	7.40	0.76	0.057
41	Squids	Invertebrate	3.92	0.600	7.00	12.00	0.98	
42	Octopus	Invertebrate	3.45	1.900	1.90	6.76	0.68	
43	Manatee	Mammal	2.02	0.002	0.06	27.38	0.00	
44	Whales	Mammal	3.60	0.100	0.03	4.62	0.00	
45	Dolphins	Mammal	4.44	0.002	0.08	10.85	0.62	
46	Seabirds	Bird	3.53	0.005	5.40	80.00	0.28	
47	Sea turtles	Reptile	2.98	0.006	0.15	22.00	0.79	
48	Invertebrates	Invertebrate	2.14	12.190	12.25	65.00	0.80	
49	Zooplankton	Invertebrate	2.25	2.500	50.21	150.70	0.84	
50	Sponges	Invertebrate	2.29	0.410	0.44	10.57	0.80	
51	Corals	Invertebrate	2.12	1.300	1.09	4.23	0.94	
52	Phytoplankton	Producer	1.00	3.020	157.04		0.59	
53	Macroalgae	Producer	1.00	10.240	13.25		0.95	
54	Seagrasses	Producer	1.00	6.870	100.00		0.80	
55	Detritus	Detritus	1.00	50.480			0.16	

(see [Appendix 2](#)) indicated that the system could be considered resilient (low Ascendency) and mature (low P/R, high cycling; [Odum, 1969](#)). The temporal trends of the ecological indicators varied according to the scenarios and vulnerability values. Overall, ecological indicators associated with the maturation and metabolism of the ecosystem varied less than indicators related to the biomass of the food web components ([Fig. 6](#)). Temporal trends of ecological indicators derived from the baseline models were overall neutral ([Appendix A, Table A7](#)).

None of the 16 ecological indicators varied consistently in climate scenarios under bottom-up dominance (v1 parameter). On the other hand, five ecological indicators varied consistently in the v2 (mixing control), v7 (top-down dominance), and vTL parameters (predators farther from carrying capacity than their prey). The temperature rise

corresponded to temporal declines in P/R, FCI, Ascendency, and mean fish weight (a proxy for the dominance of large fish species) while also coinciding with an increase in invertebrate biomass.

The mean weight of fish was strongly associated with fishing effort scenarios, increasing in scenarios of lower pressure and decreasing in the other scenarios of higher pressure. Similar patterns were observed for trophic levels, which increased with lower fishing pressure and decreased with higher fishing pressure in three (v1, v2, vTL) out of the four assumptions of food web structure. All the other ecological indicators did not vary when assumptions were top-down dominance (v7) and lower bottom-up control for predators (vTL). The temporal trends of the ecological indicators tended to differ between bottom-up (v1) and mixing control (v2) assumptions.

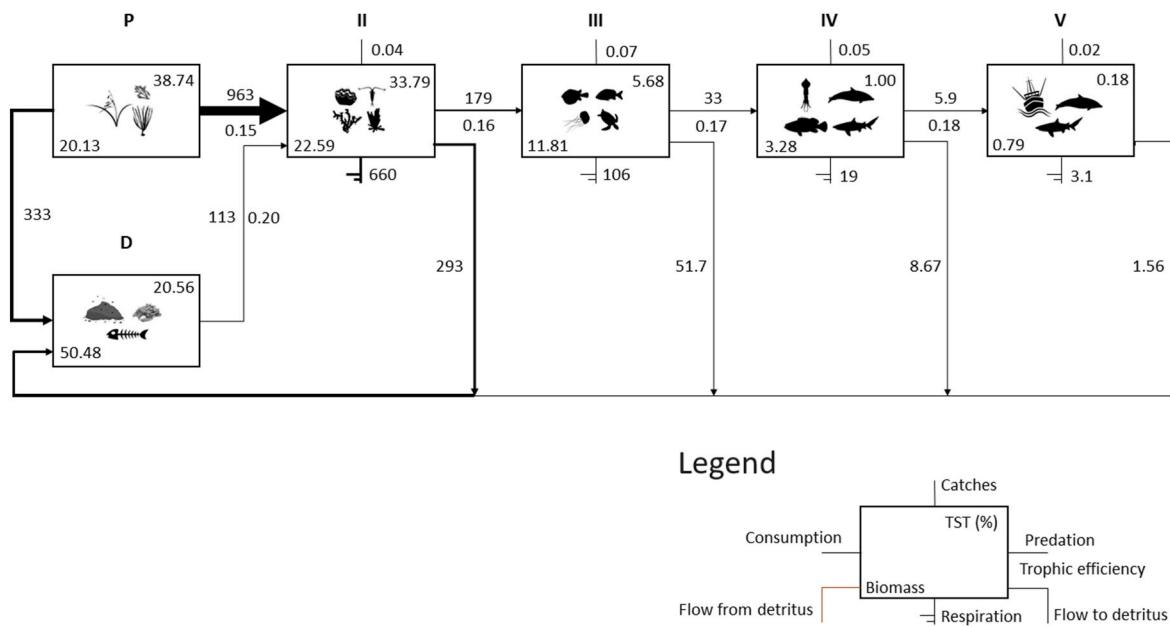


Fig. 2. Lindeman spine diagram for the model of the Brazilian Northeastern coast. D – Detritus, P – Primary producers, II – Second trophic level, III – Third trophic level, IV – Fourth trophic level, V – Fifth Trophic level. Line width is proportional to the magnitude of flow. TST: Total System Throughput (%).

4. Discussion

The Ecopath model developed here suggests that the Brazilian Northeastern continental shelf ecosystem is a grazing-based system with high biomass of multicellular (macroalgae and seagrass) and unicellular autotrophs (phytoplankton) that support diverse assemblages of consumers. Our simulations indicated that increases in temperature and fishing effort, particularly at more extreme values, may impact fish biomass and ecosystem functioning and structure. Our hypothesis was partially corroborated as warming temperatures were linked with the dominance of smaller fish species (or functional groups), and higher fishing pressure was associated with the dominance of smaller fishes with low trophic levels. Overall, these results were consistent across different assumptions of food web functioning and when incorporating the uncertainty associated with parameter values. However, despite the simulated scenarios, some ecological indicators (e.g., P/B) were not sensitive enough to change. Our findings underscore the risks of over-exploitation and climate change to tropical coastal regions. They offer valuable insights for decision-makers, managers, and stakeholders, preparing them for the rapidly evolving conditions anticipated shortly.

Our findings indicate that large top predators, such as sharks, stingrays, and groupers, are more impacted by fishing pressure and rising temperatures. These community responses, predicted by our model, align with established ecological theories (e.g., fishing down the food web, temperature-size rule, and gill oxygen limitation; Atkinson, 1994; Pauly, 2021; Pauly et al., 1998), though the underlying mechanisms may differ. Large-body predators are usually less abundant, grow slow, eat more, have late maturity, lower fecundity, and lower relative gill surface area, traits that make them less resilient to fishing (Winemiller, 2005) and less competitive at higher temperatures (Daufresne et al., 2009). Although there are mixed pieces of evidence regarding the reduction in dominance of large fish species with climate change processes in marine ecosystems (Audzijonyte et al., 2020; Jeffrey et al., 2017), traits linked with growth, maturation, and lifespan have been shown to form a fast-slow continuum at broad spatial scales due to natural gradients in temperature (Beukhof et al., 2019). On the other hand, the decline in mean trophic level and the decreasing dominance of large fish species (or functional groups) with increasing fishing pressure has been found in marine communities across the globe (Pauly et al., 1998), including the Brazilian coast (Freire and Pauly, 2010).

Large top-predators provide essential ecosystem functions (e.g., habitat coupling, herbivory control; Atwood and Hammill, 2018; Rooney et al., 2008), and their loss may trigger strong trophic cascades that alter the entire structure of marine ecosystems (Estes et al., 2011). This is the case on the Brazilian Northeastern coast, as our model suggests that the system is vulnerable to the biomass loss of predatory species, such as sharks, snappers, and mackerels. For example, we observed that, at warmer temperatures, the biomass of invertebrates tended to increase following the decline of predatory fishes, highlighting the latter's role in controlling the biomass of prey populations. Although some invertebrates, such as lobster and shrimps, are essential for fisheries, the loss of predatory fishes is also likely to impact fishers as these species are historically widely exploited and have a high market value (Frérou and Ferreira, 2005; IBAMA, 2007; IBGE, 1989).

Our modeling approach revealed minimal temporal change in the total biomass of target species across different fishing scenarios. This suggests that while some target species are sensitive to fishing pressures, most are unaffected. Interestingly, fishing pressure may paradoxically increase the biomass of certain target species by reducing the biomass of competitors and predators (Jennings and Kaiser, 1998). Since the most affected species are top predators, the reduction in predation on smaller species may have (over)compensated for the losses caused by fishing, especially under assumptions of top-down dominance. The model does not account for potential fishing adaptation towards smaller species, which may explain why their biomass remained relatively stable throughout the simulation. Another possibility is that our study may have underestimated the parameters related to fishing pressure. Although we used official estimates to quantify fishing pressure, previous studies have indicated signs of overexploitation in certain fish stocks (Oceana, 2022). Only new, comprehensive monitoring data can clarify the role of fisheries in ecosystem structure and test the accuracy of our predictions.

We found that target species declined more often in the RCP2.6 scenario than in the RCP4.5 scenario. This is counterintuitive, but it could be the result of two distinct, non-mutually exclusive processes. First, RCP4.5 may have shifted species away from the lower suboptimal temperatures found in RCP2.6, while not pushing them toward the higher suboptimal temperatures associated with RCP8.5; indeed, this is the case for *Hyperoplus* spp. Second, RCP2.6 may have experienced stronger top-down processes than RCP4.5, with a higher density of

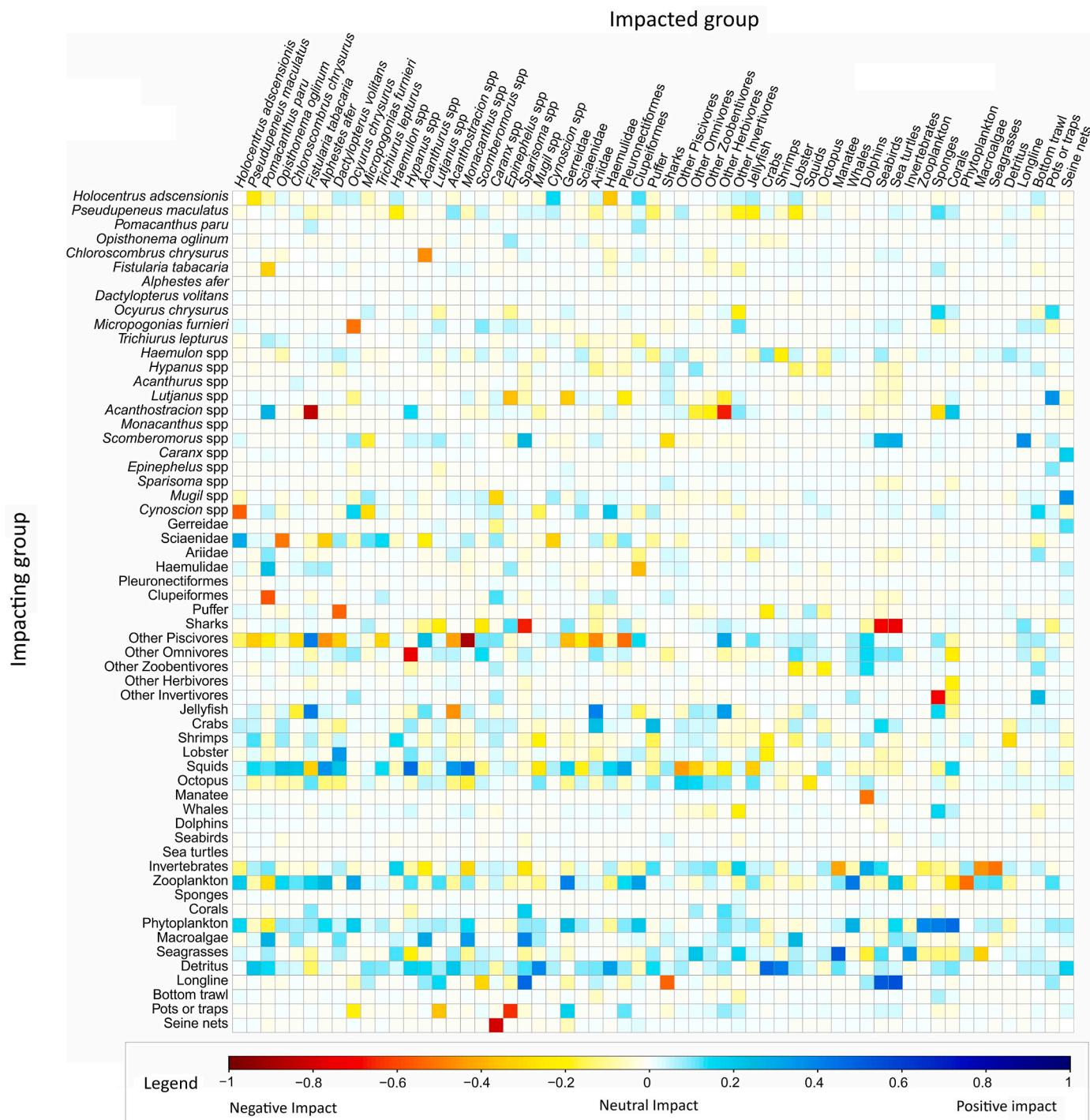


Fig. 3. Mixed Trophic Impact (MTI) analysis of the model of Brazilian Northeastern coast. Negative and positive impacts are represented in red and blue, respectively. Neutral relationships are highlighted in white. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

predators leading to a decline in the biomass of their prey at lower trophic levels, as observed in *Chloroscombrus chrysurus* and other Clupeiformes. Either way, the most likely climate change scenario (RCP4.5; Burgess et al., 2023) may have a limited impact on the ecosystem, as declines in some species are compensated by increases in others, maintaining overall biomass stability.

Although some threatened species include predatory species targeted by fisheries (e.g., sharks and groupers), most show neutral responses to rising temperatures and increasing fishing pressures. In other words, the decline of these predatory fishes was counterbalanced by the increase in

the abundance of some threatened invertebrates, such as crabs (*Cardisoma* spp., *Ucides* spp.), lobsters, and corals, and the neutral response of manatees and sea turtles. However, this result should be interpreted carefully for two main reasons. First, we only applied environmental response functions for fishes, and therefore, we are only assessing the indirect impacts of warming temperatures on the other taxa. Second, our climate scenarios are focused on temperature changes. Although this is the main consequence of climate change, the scenarios do not consider other conditions that are expected to change with higher emissions of fossil fuels, such as ocean acidification and hypoxia (Cheng et al., 2022).

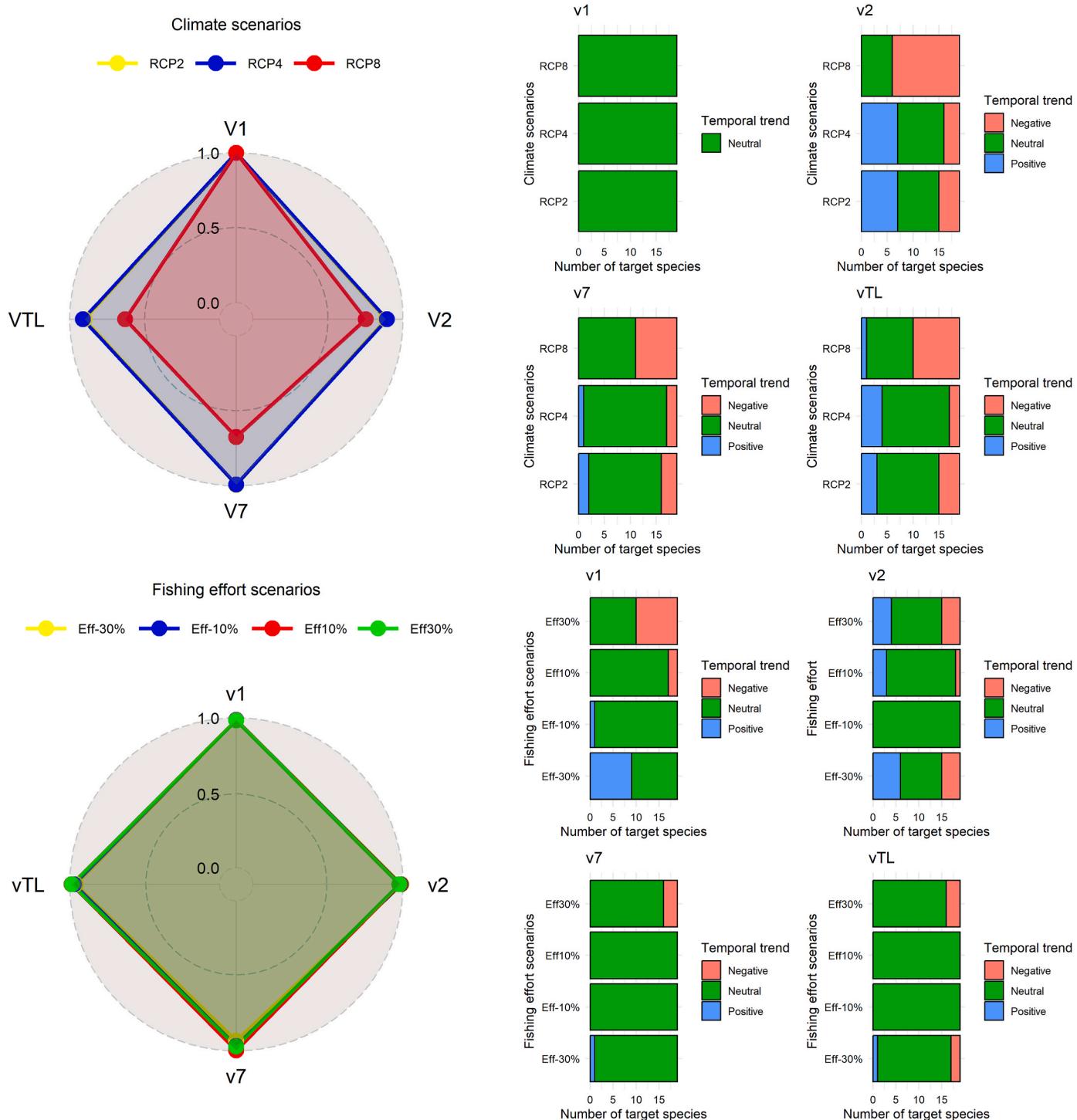


Fig. 4. The radar plots show proportional biomass changes for climate (top) and fishing effort scenarios (bottom). Values close to the circle mean no change. v1 (food web controlled predominantly by bottom-up process), v2 (food web controlled similarly by top-down and bottom-up processes), v7 (food web controlled predominantly by top-down process), and vTL (bottom-up process is more intense at the base of the food web) represent different vulnerability values scenarios (see section 2.2.5). The bar plots depict the count of target species showing negative, neutral, or positive temporal trends under different climate and fishing effort scenarios simulated until 2100. The consistency of trends was assessed using 100 Monte Carlo simulations. Trends were deemed neutral if the 90% confidence intervals of biomass rate of change encompassed 1, positive if above 1, and negative if below 1.

For example, benthic invertebrates, like crabs and lobsters, may decline with climate change due to limited adult mobility and a higher prevalence of oxygen-deficient zones on the seafloor (Hare et al., 2016; Oschlies, 2021). On the other hand, large areas of corals are likely to perish due to ocean acidification (Doney et al., 2009), heatwaves (Duarte et al., 2020), and other factors not necessarily linked with

climate change, such as pollution, overharvesting, and physical destruction (e.g., trampling during tourism activities) (Hoegh-Guldberg et al., 2017). The extent to which marine organisms, especially invertebrates, can cope with and adapt to warming temperatures and other changes induced by climate change remains unknown mainly (Alter et al., 2024; Doney et al., 2009; Moritz and Agudo, 2013). Future

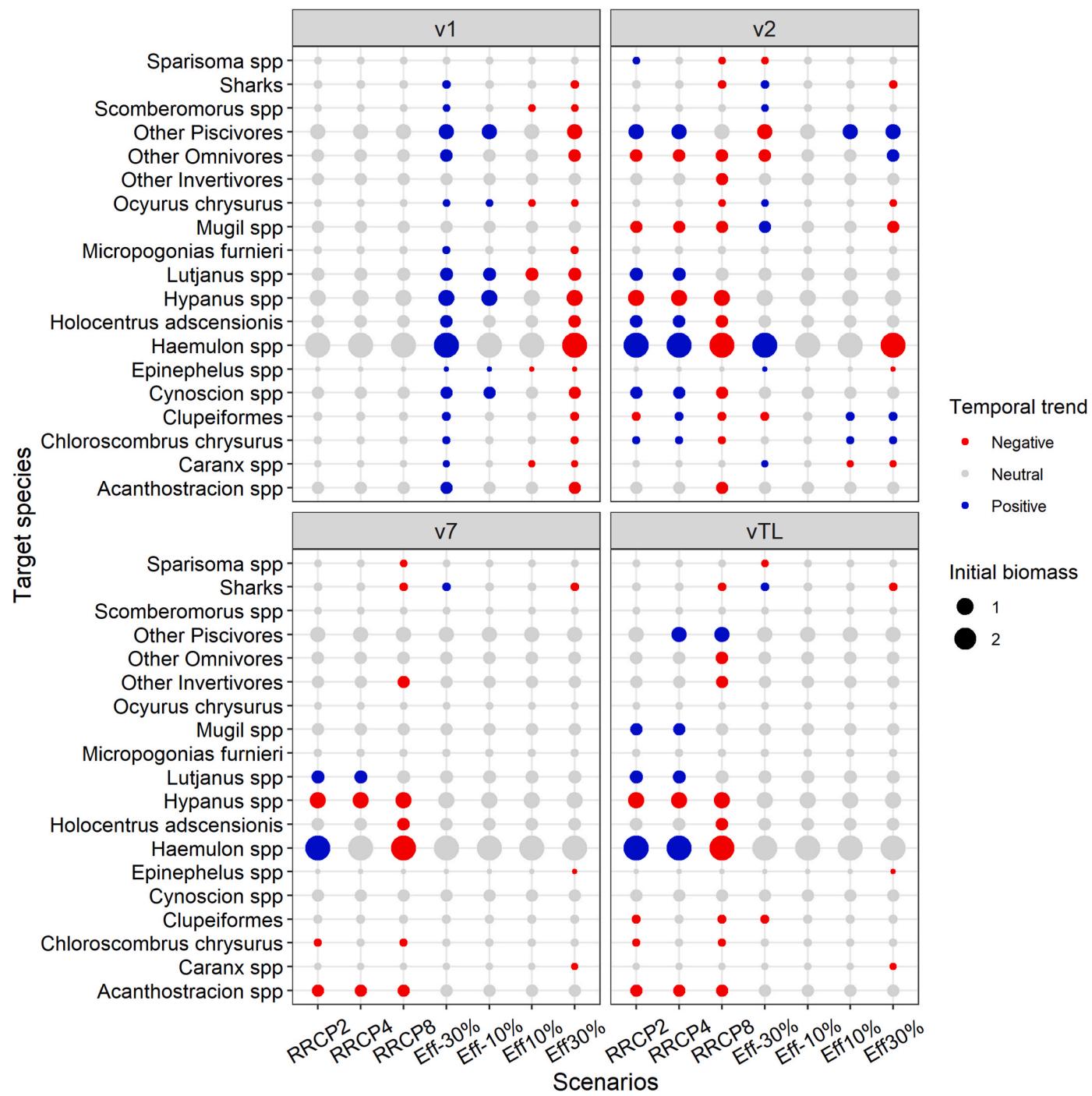


Fig. 5. Temporal trend for each target species in each scenario. Scenarios: Climate change (RCP2 [0.42 °C], RCP4 [1.53 °C], and RCP8 [4.02 °C]) and fishing effort (+10%, +30%, 10% decreasing [Eff10 d], and 30% decreasing [Eff30 d]). The consistency of the temporal trends was accessed through 100 Monte Carlo simulations. Trends were considered neutral if the 90% confidence intervals of the biomass rate of change (i.e., Species biomass in 2100/Species biomass in 2014) included 1, positive if they were above 1, and negative if they were below 1. Circle size is proportional to the initial biomass of each target species. v1 (food web controlled predominantly by bottom-up process), v2 (food web controlled similarly by top-down and bottom-up processes), v7 (food web controlled predominantly by top-down process), and vTL (bottom-up process is more intense at the base of the food web) represent different vulnerability values scenarios.

studies should prioritize this aspect to establish more robust and accurate ecosystem models.

Previous studies have demonstrated that ecological network and information metrics (e.g., P/B, cycling) may change due to climate change (e.g., Gomes et al., 2024) and fishing pressure (e.g., Bentorcha et al., 2017). Here, these metrics were less sensitive than those associated with specific components' biomass. This result suggests that the ecosystem structure and functioning of the Brazilian Northeastern coast

exhibit a degree of resilience to these two pressure disturbances despite the potential for significant declines in individual components. The inherent resilience of the system may be a sub-product of its structure (Ito et al., 2023). For example, the Brazilian Northeastern coast hosts complex and diverse marine communities, particularly those associated with coral reefs (Parravicini et al., 2013; Tittensor et al., 2010). The high species diversity has been identified as a crucial element contributing to ecosystem resilience to disturbances, as multiple species provide

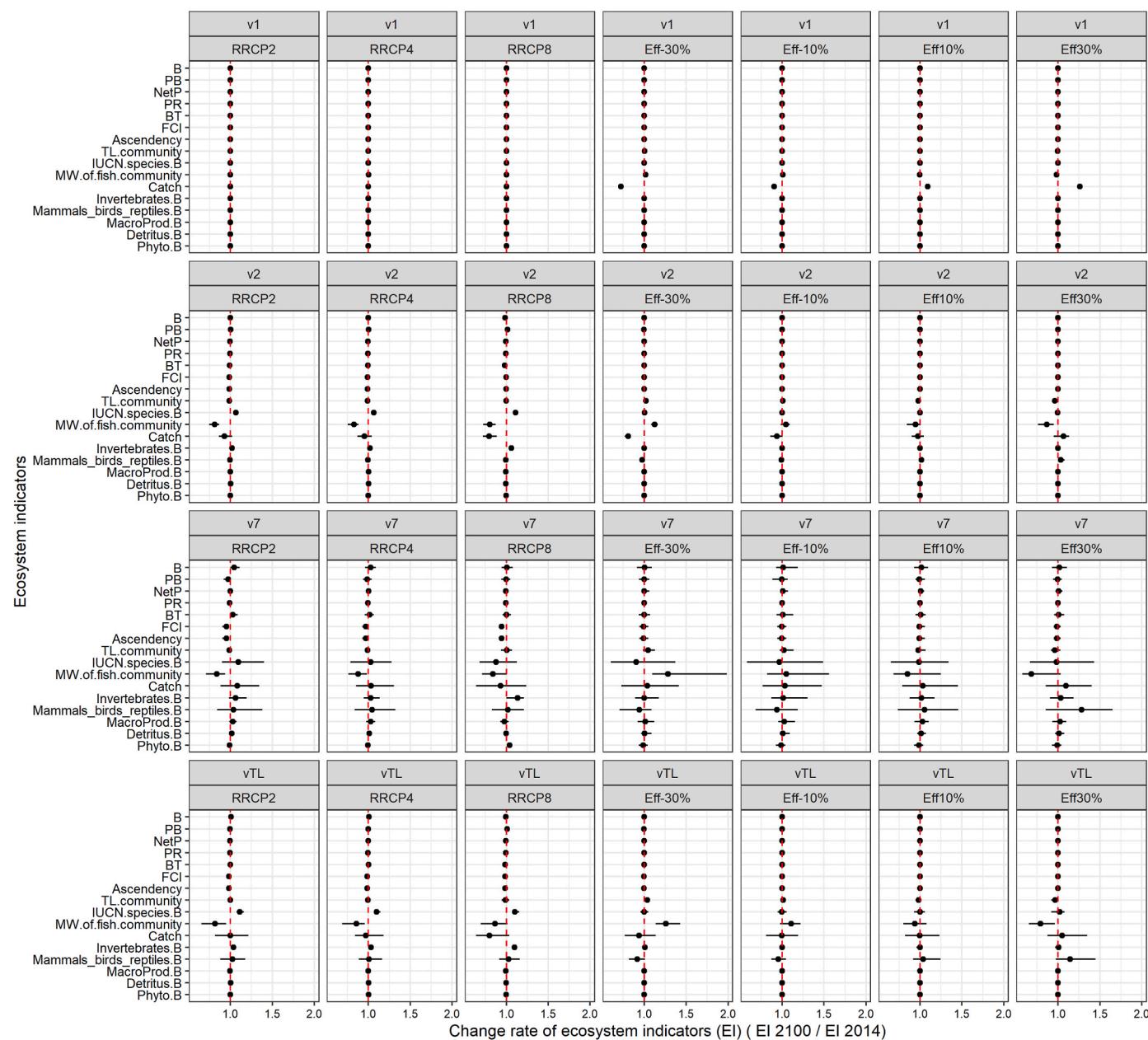


Fig. 6. The change rate of each ecosystem indicator (EI) in each scenario of climate change (RCP2 [0.42 °C], RCP4 [1.53 °C], and RCP8 [4.02 °C]) and fishing effort (+10%, +30%, 10% decreasing [Eff10 d], and 30% decreasing [Eff30d]). The change rate of each EI was calculated by dividing its value in 2100 by its value in 2014. Values close to 1 mean no change. v1 (food web controlled predominantly by bottom-up process), v2 (food web controlled similarly by top-down and bottom-up processes), v7 (food web controlled predominantly by top-down process), and vTL (bottom-up process is more intense at the base of the food web) represent different vulnerability values scenarios (see section 2.2.5). The consistency of the temporal trends was accessed through 100 Monte Carlo simulations.

redundant ecosystem attributes and services (Oliver et al., 2015).

However, we observed that rising temperatures corresponded to slight declines in P/R (balance between production and maintenance cost), FCI (amount of material cycling), and ascendancy (amount of trophic specialization, internalization, and cycling). The reductions in P/R and cycling are likely linked to increased respiration rates and metabolic costs associated with elevated temperatures (Barneche et al., 2021). While this mechanism isn't directly integrated into the equations of the Ecopath model, it manifests through compositional changes in the community. Specifically, warmer temperatures favor smaller species, which incur higher maintenance costs per gram of mass (Brown et al., 2004). Conversely, the decline in ascendancy may stem from various processes, including diminished cycling and reduced energy and matter transfer, as trophic interactions become less efficient (Rall et al., 2010).

Our simulation approach focused on the independent impacts of climate change and fishing efforts on the Brazilian Northeastern coast ecosystem to understand cause-effect relationships better and explore different magnitudes for each driver. However, changes in climate conditions and fishing efforts may co-occur as the human population grows in the region (IBGE, 2024) and temperature rises with global fossil fuel emissions (IPCC, 2023). Although in this study we avoid conducting combined scenarios as it would exponentially increase the number of simulations (i.e., climate × fishing × vulnerabilities × 100 iterations), other studies worldwide have shown that overfishing can exacerbate the effects of climate change (Lam et al., 2020; Ling et al., 2009; Sumaila and Tai, 2020). In this sense, it is reasonable to assume that the results reported here (e.g., decline of large body species) are initial and can be amplified by the combined effects of climate change and fishing efforts.

We faced challenges in calibrating and validating our model due to the absence of consistent time series data for the Brazilian Northeastern coast. To address this issue, we took measures to enhance the robustness of our conclusions. This included testing the sensitivity of our model by embracing parameter uncertainty and exploring various vulnerability values. Vulnerability values are crucial in our model as they determine the extent to which predation mortality can fluctuate in response to changes in predator biomass (Walters et al., 1997). Uncertainty in biomass and ecosystem indicators was considerably lower for vulnerabilities v1 (bottom-up control) and v2 (mixing control) when compared to v7 (top-down dominance) and vTL (predators farther from carrying capacity than their prey). This is expected as models with high vulnerability values perform as a typical mass-action model with Lotka–Volterra dynamics (Rehren et al., 2022). Although we found patterns consistent across different vulnerabilities, our results also highlight the importance of state and national agencies conducting monitoring programs of marine communities and fish landings to guide better modeling efforts and the overall assessment and management of natural resources.

Despite the challenges of modeling data-poor systems, this study demonstrates how warming temperatures and increasing fishing pressure can significantly affect tropical coastal ecosystems. These findings aim to stimulate discussions about the future of coastal ecosystems in Brazil and other data-poor regions, emphasizing the importance of ensuring resource sustainability and maintaining ecosystem services. Strategies such as promoting economic diversification in fishing communities (e.g., ecotourism and game fishing), adjusting fishing quotas, establishing marine protected areas, and advancing environmental education can help mitigate the impacts of declining fish stocks on livelihoods and reduce fishing pressure on vulnerable species, including key predators like sharks. Finally, the potential ramifications of species relocating to match their optimal environmental conditions on local ecosystems remain to be fully understood, a phenomenon that could be explored by integrating species distribution forecasts and spatial-temporal ecosystem modeling.

CRediT authorship contribution statement

Ronaldo Angelini: Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Maria Alice Leite Lima:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Alex Souza Lira:** Writing – review & editing, Investigation, Formal analysis, Conceptualization. **Flávia Lucena-Fréduo:** Writing – review & editing, Investigation. **Thierry Fréduo:** Writing – review & editing, Investigation, Conceptualization. **Arnaud Bertrand:** Writing – review & editing, Investigation. **Tommaso Giarizzo:** Writing – review & editing. **Jeroen Steenbeek:** Writing – review & editing, Formal analysis. **Marta Coll:** Writing – review & editing, Formal analysis. **Friedrich Wolfgang Keppler:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization.

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Declaration of competing interest

The authors declare that the research was conducted without any commercial or financial relationships that could potentially create a conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.marenvres.2024.106909>.

Data availability

Model is available in Ecobase. We also included tables in the supplementary material with information about the parameters used in the model.

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