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Beach-cast algae communities as a proxy for evaluating coastal water eutrophication

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ABSTRACT

Coastal ecosystems, located at the intersection of land and sea, are subject to multiple human-induced stressors that affect both terrestrial and marine environments. Among the 12 core priorities of global policies and biosphere monitoring efforts, eutrophication indicators play a key role. However, developing and implementing these indicators at high resolution and large spatial scale poses significant logistical, technological, and economic challenges. Satellite-based chlorophyll-a measurements provide insights into the immediate effects of coastal eutrophication, but assessing its impacts on benthic habitats remains a significant hurdle. An alternative lies in examining beach-stranded materials, particularly macrophyte wracks, which may serve as proxies for shifts in the diversity and composition of coastal benthic habitats. This study explored whether macroalgae communities in beach wracks reflect the condition of marine habitats affected by coastal eutrophication. Using empirical data (for 84 taxa on 212 sites), two community-level indicators were developed: Community Turbidity Tolerance (CTTI) and Community Thallus Length, derived from algae found in beach wracks. Both indicators were shown to correlate with coastal chlorophyll-a concentrations, a widely used proxy for eutrophication. Both metrics also aligned with trends in the Water Strategy Framework Directive's Good Ecological Status (GES) indicator, even though the CTTI only had a significant relationship with extreme GES levels. The macrophyte wracks derived indicators of coastal eutrophication we developed here further promise increased sampling resolution, cost-efficiency, and logistical simplicity. Moreover, beach wrack monitoring offers strong potential for inclusion in citizen science programs, further enhancing its scalability and impact.

1. Introduction

Worlds' coastlines are 1,163,701 km long (Burke et al., 2001) and coastal ecosystems are believed to provide approximately 70 % of global ecosystem services (Costanza et al., 1997; Martínez et al., 2007). Human populations have thus long been attracted to coastal

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areas, which already hosted more than 40 % of the world population in the early 2000s (Small and Nicholls, 2003). As a result, human footprint on marine ecosystems peaks at coastal locations (Halpern et al., 2008). It is estimated that all the coastal regions in the world are under human influence, and that 60 % of coastal ecosystems face high human pressures (*i.e.* 0–20 % intactness, Williams et al., 2022). In light of the expected increase in the human population within the low elevation coastal zone by 2050 (Merkens et al., 2016), mitigating human pressures on coastal ecosystems appears urgent (Pinheiro et al., 2019).

Coastal ecosystems are part of the land-sea continuum and are therefore exposed to multiple human stressors affecting both terrestrial and marine environments (Crain et al., 2009). These cumulated pressures result, *inter alia*, in the coastal eutrophication syndrome (Le Moal et al., 2019), a nexus of complex biogeochemical responses to the increased availability of limiting nutrients (Doney, 2010), ultimately leading to hypoxic dead zones (Diaz and Rosenberg, 2008). These responses depend on climate, habitats, biomasses, and community dynamics, which are all affected by ongoing global changes. Human induced eutrophication of coastal ecosystems is therefore difficult to evaluate at large scale (Malone and Newton, 2020).

To describe human pressures on ecosystems state and monitor the effectiveness of societal responses at large scales, the development of ecological indicators is promoted (European Environment Agency, 1999; OECD, 1993). Eutrophication indicators are among the 12 central nodes of current global policies and biosphere monitoring initiatives toward this objective (Chandrakumar and McLaren, 2018), and regional policies were developed to stimulate their development and monitoring at national and regional scales. In Europe, enhancement of coastal marine ecosystems governance is the focus of the Marine Strategy Framework Directive (MSFD, 2008/56/EC, Long, 2011). This framework promotes the implementation and monitoring of ecological indicators as defined by the earlier Water Framework Directive (WFD, 2000/60/EC). However, existing eutrophication monitoring methods are subject to multiple limitations in terms of technology, economy, and other aspects when applied at high resolution and large scale (Patrício et al., 2016).

Yet, some opportunities exist for monitoring eutrophication in coastal marine ecosystems while overcoming several sampling constraints. The use of remote sensing data has been demonstrated a promising and powerful method to trace human-derived nutrient disposal at sea (Maúre et al., 2021). For instance, remote sensing reflectance correlates with Chlorophyll-*a* concentration (Hu et al., 2019). Satellite spectroradiometry can thereby be used to map the density of bentho/demersal and planktonic marine primary producers that are highly sensitive to nutrient loads (Woodland et al., 2015). This approach is extremely valuable for the production of eutrophication indicators within the MSFD (Gohin et al., 2019) but is not self-sufficient, at least because underlying algorithms are dependent on empirical data (Werdell and Bailey, 2005). Whereas remotely sensed chlorophyll-*a* monitoring informs on the proximal effects of coastal eutrophication, cascading effects on higher trophic/ecosystemic levels are still challenging to monitor at large-scale. An opportunity for such monitoring may lie in beach stranded materials, by looking at macrophyte wracks as a proxy of changes affecting the diversity and composition of coastal benthic habitats (Thibault et al., 2022). Macroalgae are benthic photosynthetic organisms that participate in the marine nutrient uptake. In coastal ecosystems, they provide habitat, food, and nursery grounds while regulating primary productivity and nutrient cycling (Steneck et al., 2013). On land, inorganic debris of marine litter are already used as coastal pollution descriptors to produce indicators of the Good Environmental Status (GES) of coastal ecosystems (Federigi et al., 2022). Further identification of organic debris from benthic macroalgae would enable more data to be collected on the characteristics of coastal ecosystems and the effectiveness of marine policies. (Jacob et al., 2020).

This study aims to explore whether beach algal communities can serve as effective proxy indicators for coastal eutrophication, in order to provide a new, low - cost, and easy - to - operate method for global coastal ecological monitoring. The sensitivity of macroalgae cover and composition to nutrient availability in seawater make them relevant indicators of the GES of coastal waters (Scanlan et al., 2007). Given that they constitute a substantial part of macrophyte wracks on beaches (Orr et al., 2005), presumably originating from proximate coastal donor habitats (Suursaar et al., 2014), we hypothesized that beach wrack macroalgae communities may hold information on the state of marine habitats as a response to coastal eutrophication. This is what is tested here, using data from an empirical sampling of beach wracks macroalgae. We first developed a community weighted mean index of tolerance to turbidity based on species functional traits compiled in the European AlgaeTraits database (Vranken et al., 2023), that we tested against remote sensing Chlorophyll-*a* concentration as a proxy of coastal eutrophication. We expected a positive relationship between our trait-derived index of tolerance to turbidity and Chlorophyll-*a*. Because macroalgae display variable responses to increased nutrient availability (Strain et al., 2014), we investigated the response of the three dominant taxonomic branches of beach-cast macroalgae *Phaeophyta*, *Chlorophyta* and *Rhodophyta* both together and separately. As eutrophication also correlates with the rise of turf dominated algal communities (Filbee-Dexter and Wernberg, 2018), we then computed a community weighted mean index based on taxa thallus length, and hypothesize a negative relationship with Chlorophyll-*a* concentration. Finally, we assessed the relevance of both indices within the scope of regional policies by exploring potential covariation with a GES indicator of the MSFD previously compiled for the same water bodies, expecting the "very good state" of GES to be associated with low values of Community Tolerance to Turbidity Index and high values of Community Thallus Length.

2. Methods

2.1. Sampling design

From August to December 2020, we sampled freshly stranded macrophyte wracks on 212 beaches along the Channel and Atlantic coast of the French Brittany peninsula (Fig. 1). This design was chosen to encompass a wide variety of land-to-sea interface contexts, while lowering the risk of harsh temporal bias associated to coastal macroalgae phenology. At each beach site, we sampled five 1 m^2 quadrats spaced 5 m apart along a 25 m transect positioned along the freshest wrack line (closest to the shore). Within each quadrat, all macrophyte fragments were visually identified to the lowest possible taxonomic rank and categorized into three taxonomic subgroups:

Phaeophyta, *Rhodophyta*, and *Chlorophyta*. The relative frequency of each taxon occurrence was then compiled at the site scale (values from 0 to 5; 0: taxon not observed in any quadrat, 5: taxon observed in all quadrats).

2.2. Trait-based community indicators of eutrophication

For each taxon, we then derived a "Tolerance to Turbidity index" (TTI) from the AlgaeTraits database (Vranken et al., 2023). All taxa included in this database were re-classified as either intolerant (1), moderately tolerant (2) or tolerant (3) to turbidity, based on the "tolerance to pollutants" trait. Taxa found in "clear" or "oligotrophic" waters according to AlgaeTraits were attributed a TTI value of 1. Taxa found in the full range of conditions from "clear" to "turbid" waters were attributed a TTI value of 3. The remaining taxa were attributed an intermediary value of 2. From the same database, we compiled the value of the Maximum Thallus Length (MTL) for each species that we identified in beach wracks. Full list of the 84 taxa considered, along with their value for the "Tolerance to Turbidity index" ($N = 52$) and thallus size ($N = 68$) is provided in Supplementary Table 1.

We then computed for each beach site a "Community Tolerance to Turbidity Index" (CTTI), i.e. a community-weighted mean index (Díaz et al., 2007) based on each taxon TTI and the relative frequency of each taxon occurrence across the five quadrats, as a site-level proxy for the "tolerance to turbidity" of the algae community that we found in macrophyte wracks. This index was calculated for the whole algae community as well as for the three underlying taxonomic branches, to account for specific responses to environmental gradients. High value of CTTI should be interpreted as communities dominated by species tolerant to turbidity. We also computed a community weighted "Thallus Length" index (CTL), including all macroalgae taxa, to account for the average canopy height of algae communities that we identified at each site from the macrophyte wrack sampling.

2.3. Remote-sensing environmental predictors

Environmental data were obtained from MARS3D and WaveWatch model simulations of the "Modelling and Analysis for Coastal Research" project (MARC, https://marc.ifremer.fr). These included the sea-surface temperature (SST) at 2.5 km resolution (Lazure and Dumas, 2008), Chlorophyll-*a* total concentration at 4 km resolution (Menesguen et al., 2014), and waves height at 2.5 km resolution (Tolman, 2008). These three environmental layers were acquired as netcdf files, and handled with "ncdf4" package in R (Pierce, 2024). Each beach wrack sampling was associated with the mean value of these latter three environmental predictors, averaged for the

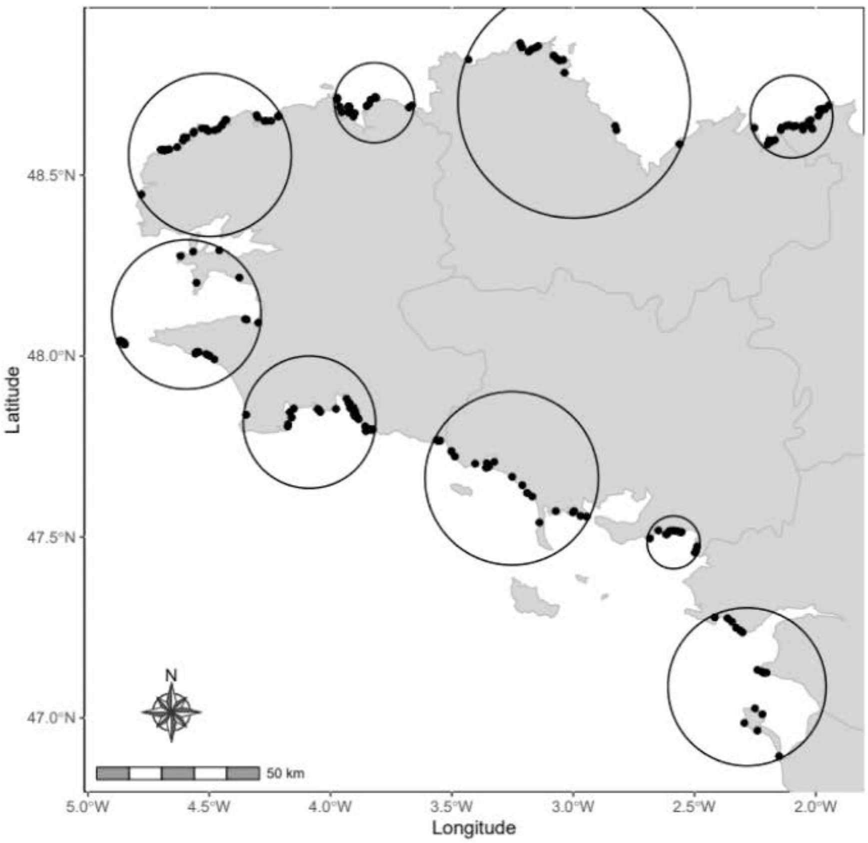

Fig. 1. Distribution of beaches where beach-cast macroalgae were sampled. The circles represent the geographical clusters considered for the modeling.

sampling month and across all raster cells included in a 3 km offshore marine buffer. Monthly mean of environmental data was used to lower the potential biases associated with diurnal and tidal variations in SST, punctual blooms of Chlorophyll-*a* and climate-related wave regimes including cloud obstruction (Meyer et al., 2024; Scales et al., 2017). The 3 km buffer was chosen as a compromise between the expected benthos/wrack relationship (Thibault et al., 2022) and the availability of environmental data raster cells in proximity of our study sites.

2.4. Indicators' sensitivity to observed eutrophication

We hypothetized an increase of CTTI and a decrease of CTL when Chlorophyl-a increases. To model the relationship between our wrack derived indicators (i.e. CTTI and CTL) and eutrophication (i.e. Chlorophyll-*a* concentration) of coastal waters, we computed Generalized Linear Mixed Models with R software version 4.3.3 (R Core Team, 2024) and the package "glmmTMB" (Brooks et al., 2017). CCTI and CTL values were distributed normally within each data subset so that all models assumed a gaussian family distribution of the data. For each model, variations in the CTTI and CTL were explored as responses to variations in Chlorophyll-*a* concentration. Full models also included sea surface temperature and waves height to control for their established influence on the distribution of benthic macroalgae communities (Gallon et al., 2014; Gaudin et al., 2018). Predictors had a maximum pairwise Pearson correlation coefficient of 0.5 and models were further checked for multicollinearity. Spatial autocorrelation inherited from our sampling design was accounted for by adding a random intercept effect based on geographical clusters. These clusters were obtained using a Ward clustering of geographical distance matrices using the "ClustGeo" R package (Chavent et al., 2021). From the full model, we processed all the models resulting from all the combinations of fixed effects and identified the best model using Aikake Information Criterion (Akaike, 1974). Models' quality performance, and post-hoc estimates were computed with "performance" (Lüdecke et al., 2021), "car" (Fox and Weisberg, 2019) and "emmeans" (Lenth, 2023) R packages. Statistical significance was set at $p < 0.05$.

2.5. Correlation with existing indicators

In a second step, we checked whether our CTTI and CTL could contribute to the framework of the MSFD. In particular, we expected our two indices to correlate with the general "Good Environmental Status" (GES) of the MSFD, which accounts for both the ecological and chemical states of coastal and transition waters (Bizzozero, 2020). This indicator has the advantage of being based on *in situ* measurements of physico-chemical (temperature, turbidity, oxygen, nutrients, pollutants, etc.) and biological (phytoplankton, benthos, macro-algae, plants, fishes, etc.) features. In return, such measurements are mostly limited to a few sampling sites and temporal replicates which restrict their ability to capture fluctuations in biotic ecosystem features. We expected the "very good state" of GES to be associated with low values of our CTTI and high values of CTL. We conducted a type II Analysis of Variance (ANOVA), using a Chi-squared ($\chi 2$) test to assess the statistical significance of the relationship between this aggregated discrete water quality indicator and our beach-cast derived indices.

3. Results

We identified 84 macroalgae taxa within the 212 macrophyte wracks that we sampled on sandy beaches all along the coastline of Brittany peninsula. *Phaeophyta* was the more abundant group (28 taxa on 211 beaches), *Rhodophyta* was the most diverse (50 taxa on 166 beaches) and few *Chlorophyta* taxa were largely distributed (5 taxa on 182 beaches). We were able to recover a TTI value for 54 of these on the AlgaeTrait database, 68 for the MTL trait. This subset of species included most of abundant taxa (>30 % occurrence frequency). The average TTI trait value of macroalgae was of 1.95 ± 0.27, and *Phaeophyta* and *Rhodophyta* had the highest variation

Table 1
Modeling outputs for the Community Turbidity Tolerance Index (CCTI) and Community Thallus Length (CTL). The number of taxa, wrack samples, along with the mean, standard deviation and variation coefficient of the four considered indexes are provided at the top of the table. Model estimates and their confidence intervals (95 %) of estimates are provided for all the predictors selected through downward stepAIC from the full models (see Supplementary Table 2).

	CTTI	**CTTI**			**CTL**
	All	**Phaeophyta**	**Rhodophyta**	**Chlorophyta**	**All**
Number of Taxa	54	26	23	5	68
Number of Wracks	212	211	166	182	212
CCTI	1.95 ± 0.27	1.21 ± 0.44	0.43 ± 0.28	0.47 ± 0.28	858 ± 330
Variation Coeff.	54 %	55 %	55 %	34 %	180 %
AIC Selected Models					
Chlorophyll a	**0.02 [0.00:0.04]**	−0.03[−0.07:0.02]	**0.04 [0.01:0.07]**	0.01[−0.01:0.04]	**−45.54 [−71.65: −19.42]**
Waves exposure	**−0.15 [−0.29:−0.01]**	**-**	-	-	-
Sea Surface Temperature	-	**-**	-	0.03[−0.00:0.06]	**40.43 [6.82: 74.03]**
(1|Spatial Clusters)	-	**0.18 [0.09:0.30]**	**0.11 [0.06: 0.20]**	-	-
R^2					
Marginal	0.06	0.01	0.09	0.05	0.05
Conditional	-	0.17	0.24	-	-
AIC	32.91	228,.33	20.56	45.56	3056.22

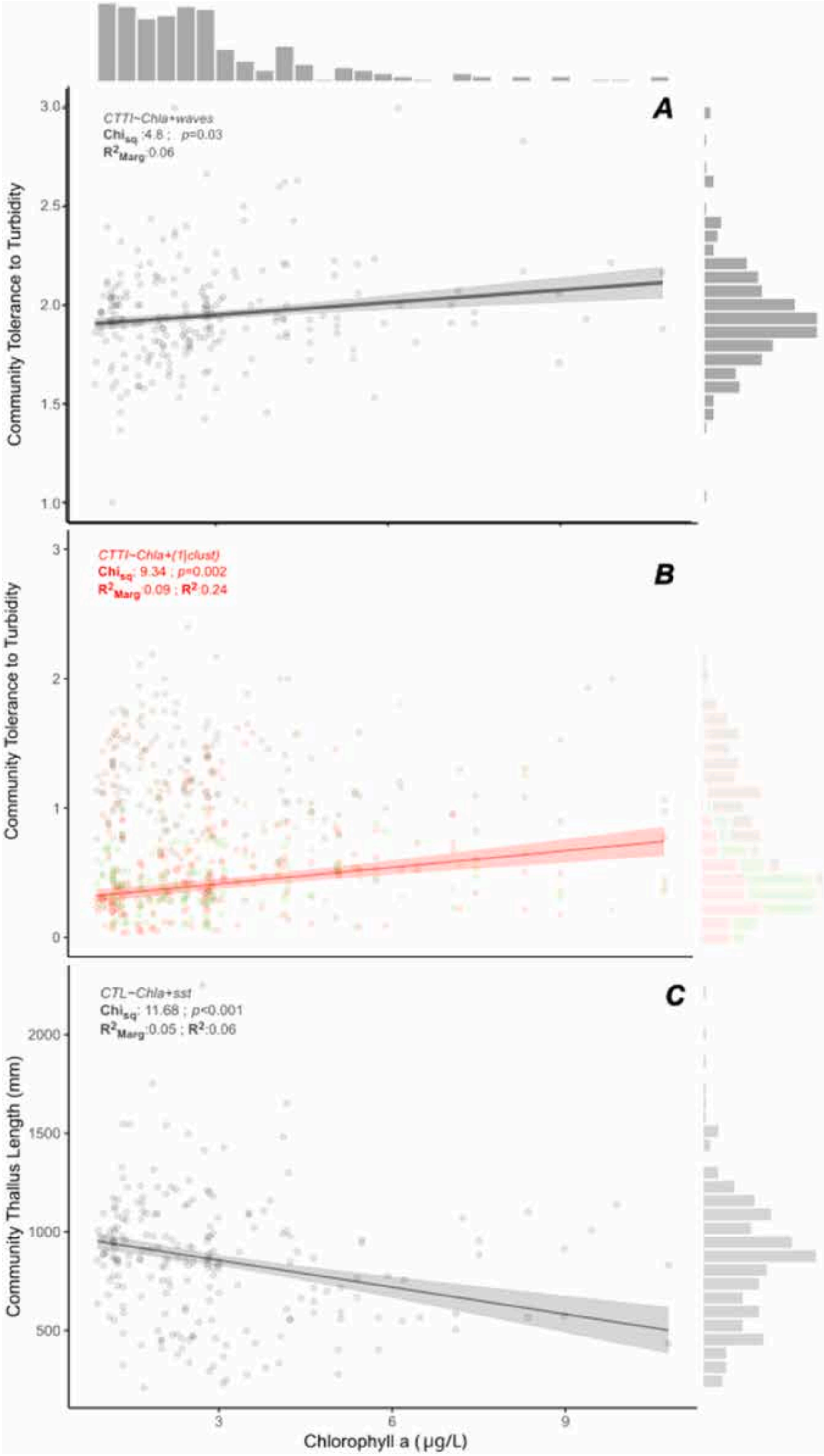

Fig. 2. Modeled linear relationships between the A) overall Community Turbidity Tolerance Index (CTTI) calculated for the whole beach-caste algae community and Chlorophyll-*a* concentration within a 3 km coastal buffer. B) Details on the relationship between the CTTI and coastal concentration in Chlorophyll-*a*, as a function of the taxonomic branch. *Phaeophyta* are colored in brown, *Rhodophyta* in red and *Chlorophyta* in green. C) Relationship between the Maximum Thallus Length of the algal community (CTL) as estimated from macrophyte wracks and the coastal concentration in Chlorophyll-*a*.

coefficient for the TTI trait (55 %) as compared to Chlorophyta (Table 1). The average taxa MTL value was 85.8 cm ± 33, but the variation coefficient for this trait was very large (180 %, Table 1). The full taxa list and corresponding Tolerance to Turbidity (TTI) and Maximum Thallus Length (MTL) values as well as taxa prevalence are provided Supplementary Table 1.

3.1. *Indicators' sensitivity to observed eutrophication*

We found evidence of a positive correlation between the CTTI calculated for the whole wrack macroalgae community (average 1,95 ± 0,27) and Chlorophyll-*a* concentration (95 %CI [0.00:0.04]) based on the model with the lowest AIC (ΔAIC 3,28; Supplementary table 2). Conversely, higher exposure to waves correlated with lower values of the CTTI (95 %CI [-0.29:-0.01]). Nor SST nor the random geographical clusters were retained in this best model by the step AIC procedure.

From our sampling of beach wracks, we found 26 *Phaeophyta* taxa among a total of 29 for which the affinity to turbidity was recorded in the AlgaeTraits database. The CTTI for this taxonomic group specifically did not correlate with any of the environmental predictors. The random intercept for the geographical cluster was the only predictor that contributed to explain variations (16 %) in the CTTI of *Phaeophyta* significantly. The Chlorophyll-*a* concentration was retained in the model with the lowest AIC (ΔAIC 3.13) but had not significant effect on the CTTI, as in the full model (Fig. 2B; Supplementary Table 2).

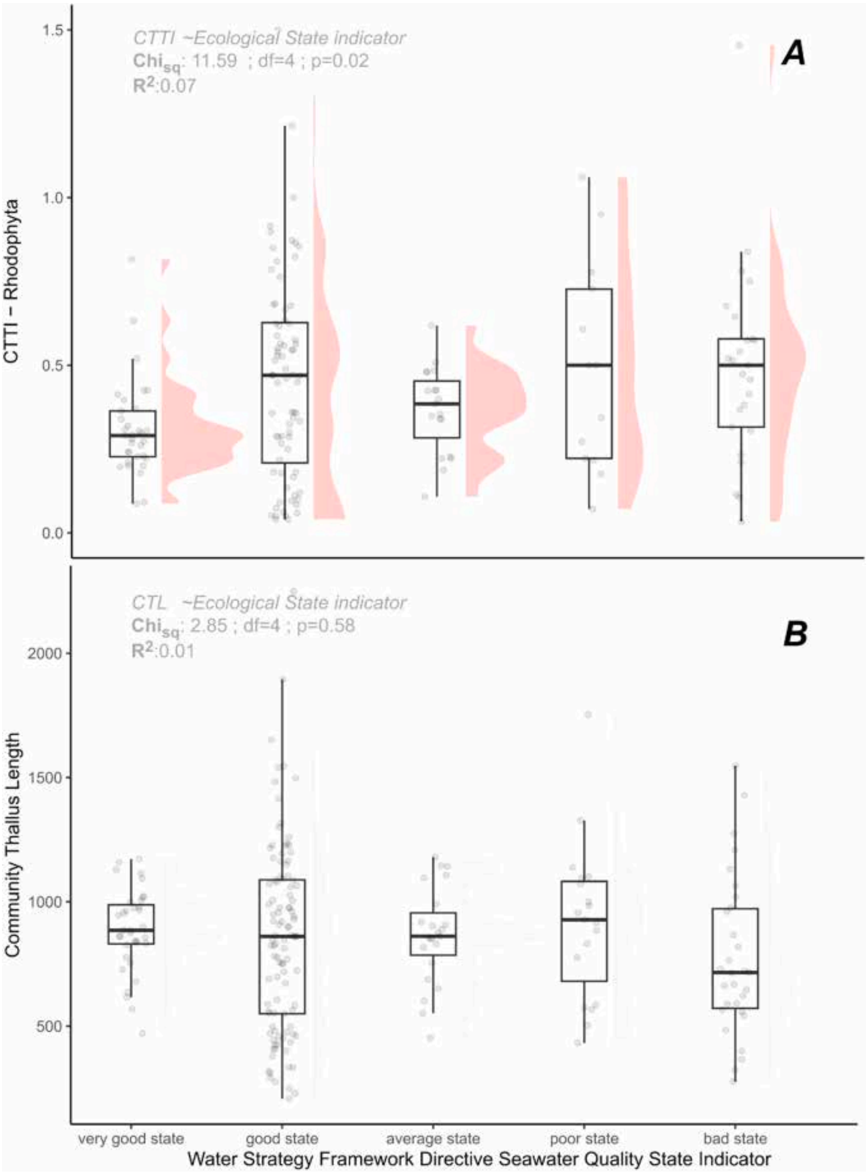

Fig. 3. Variations in A) the Community Turbidity Tolerance Index (CTTI) of *Rhodophyta*, and B) the Community Thallus Length (CTL) value generalized water quality indicator depending on the quality of coastal waters as estimated by the GES.

Even though *Rhodophyta* was the most diverse group of species in macrophyte wracks sampled (n = 50), the turbidity trait was available for only 23 of them in the AlgaeTrait database. Models accounted for the CTTI of *Rhodophyta* found on 166 beaches. Both the full and the lowest AIC models showed a positive correlation between the CTTI of *Rhodophyta* and Chlorophyll-*a* concentration, with similar estimates (95 %CI [0.01: 0.07]; Fig. 2B). As for the *Phaeophyta*, the random geographical cluster had a significant influence on the CTTI. The model with the lowest AIC (ΔAIC 3,79) only kept Chlorophyll-*a* and this random geographical clusters and explained a similar proportion of the CTTI variance (i.e. conditional R^2 24 %). According to the model with the lowest AIC, Chlorophyll-*a* concentration contributed to 9 % of variations in the CTTI of *Rhodophyta* (Supplementary Table 2).

Chlorophyta was the less diverse taxa group (n = 5) that we found in macrophyte wracks. Still, they were present on 182 beaches, and we were able to recover turbidity trait values for all of them in the AlgaeTraits database. The overall CTTI value for this taxonomic group was 0,47 ± 0,28. We did not detect any correlation between the CTTI of this group and the Chlorophyll-*a* (Fig. 2B) or any other environmental predictors we tested (Supplementary Table 2).

We found records of the MTL trait for 68 taxa among the 84 macroalgae taxa identified, so that we were able to compute a CTL index for the 212 sampled macrophyte wracks (Average: 858 ± 330 mm). The best model highlights that CTL correlated negatively with the Chlorophyll-*a* concentration (95 %CI [-73.74: −17.71], Fig. 3B), and positively with SST (95 %CI [4,41: 76,15]). Yet, models explained only 5 % of the CTL variance (Supplementary Table 2). Overall, our results show that calm and eutrophic waters host macroalgae communities dominated by turbidity tolerant and shorter taxa.

3.2. Correlation with existing indicators

As for the correlation with Chlorophyll-*a* concentration, the CTTI for *Rhodophyta* varied significantly with the exposition to coastal waters of various quality as estimated by the MSFD Good Ecological State indicator (Chisq: 11.56; $p < 0.05$; Fig. 3A, Supplementary Table 2). *Rhodophyta* macroalgae wracks from “Very Good” quality waters showed a lower CTTI for *Rhodophyta* (95 %CI [0.21: 0.40]) as compared to “Good” quality (95 %CI [0.41: 0.53]) and “Bad” quality waters (95 %CI [0.39: 0.60]). Wracks from “Average” quality waters showed intermediary values of CTTI (95 %CI [0.25: 0.50]) and those from “Poor” quality waters had the highest values of CTTI (95 %CI [0.35: 0.64]). However, only a few p-value corrected pairwise comparisons turned out to be significant as a result of high intra class variances (Supplementary Table 3).

We found no significant variations on the CTL derived from wracks’ macroalgae depending on the estimated quality of coastal waters (Chisq: 2.85; $p = 0.58$, Fig. 3B). The CTL we computed from wrack communities of macroalgae lying on “Bad” water quality shores had the lowest values (95 %CI [657: 893]). Yet, averaged values of CTL were overlapping across all five categories of water quality state (Supplementary Table 3).

4. Discussion

We developed two community-wise indicators of sensitivity to water eutrophication in benthic macroalgae from algal fragments sampled in beach wracks. We showed that i) the Community Turbidity Tolerance, and ii) the Community Thallus Length both covary with the coastal Chlorophyll-*a* concentration, a proxy of coastal eutrophication (Maúre et al., 2021). Despite our metrics following similar trends to the discrete Good Ecological Status indicator of the WFD, only the CTTI presented a significant covariation with the extreme levels of this indicator.

The CTTI, calculated for the whole wrack macroalgae community, presented a positive correlation with coastal Chlorophyll-*a* concentration. This first confirms that the CTTI, which relies on rough qualitative trait data, is sensitive to a proxy of coastal water eutrophication, which is a first step toward its validation. This confirms our hypothesis that indirect indicators such as the CTTI, developed from a functional trait related to eutrophication, may indeed be used to track coastal eutrophication gradients from beach casted macroalgae. Furthermore, this association appears to be specific as the CTTI shows a negative relationship with wave exposure, which also serves as an inverse proxy of water residence time (Abdolahpour et al., 2020), a key component of coastal eutrophication (Mari et al., 2007). This second finding is therefore coherent with our hypothesis. Altogether the sensitivity and specificity of beach wrack’s CTTI makes it a promising indicators of coastal eutrophication (Niemeijer and De Groot, 2008). Yet, the strength of CTTI dependance to chlorophyll-*a* appeared limited at the full macroalgae community scale. This was demonstrated by the low proportion of variance explained by the AIC-selected model (6 %) and the loss of correlation when additional co-factors were included. The relative contributions of macroalgae taxonomic branches to relationship between our CTTI and coastal Chlorophyll-*a* suggested that a *Rhodophyta*-derived CTTI responds more tightly to coastal eutrophication.

4.1. Presence of chlorophyta and changes in Rhodophyta species correlate with coastal eutrophication

We expected *Chlorophyta* to draw increased CTTI values at the most eutrophic locations. It has long been observed that green macroalgae quickly respond to water eutrophication resulting from human-derived nutrients reaching coastal waters (Morand and Briand, 1996). From the 1970s and the rise of agricultural intensification to today, green tides of *Ulva*—a taxon now considered bioindicator of eutrophication under the MSFD—are observed yearly along Brittany’s coasts in spring (Louis et al., 2023). Consistently, the *Chlorophyta* taxa found on beaches during our sampling were assigned the maximum turbidity tolerance index value, based on our computations from AlgaeTraits database (2.6 ± 0.9). Yet, the contribution of this group to our CTTI was very low for at least two reasons. First, the group accounts for a very small fraction of the taxa richness used to compute the CTTI (<10 %), which inherently limits its weight. Second, the high affinity of *Chlorophyta* taxa to eutrophic conditions make them specialists of such conditions

(Pérez-Mayorga et al., 2011) and thus less likely to reflect community changes across the whole eutrophication gradient.

Phaeophyta were the most abundant and widely distributed taxa group in our sampling. From the information we were able to recover in the AlgaeTrait Database, *Phaeophyta* were associated with an average turbidity tolerance value of 1.7 ± 1.0 and a 55 % variation coefficient, reflecting the taxonomic diversity of Phaeophyta and their occurrence in a variety of eutrophication levels (Harper et al., 2012). Yet, the CCTI for this group only varied between geographical clusters, which suggests that *Phaeophyta* community changes are mostly driven by biogeographical patterns. This result is in line with the documented biogeographical gradient in macroalgae composition previously highlighted along Brittany's coast through *in situ* monitoring (Derrien-Courtel et al., 2013; Gaudin et al., 2018). In a previous study, we confirmed that the spatial structuring of benthic habitats is also reflected in the similarity in beach wrack macrophyte composition at various spatial scales (Thibault et al., 2022). Here, we confirm the predominance of biogeography in shaping the community composition in stranded *Phaeophyta*, but we detected no variations in CTTI for this group as a response to various coastal eutrophication levels.

Rhodophyta were recorded in a variety of eutrophication contexts, as expected from both their coupled nutrient uptake efficiency and nutrient storage capability (Leston et al., 2008). Yet, as for the *Phaeophyta*, variations in the relative CTTI of *Rhodophyta* appeared partially driven by biogeography. This is unsurprising as biogeographical transition zones have previously been determined in the distribution of red seaweed communities (Gallon et al., 2014). However, our relative CTTI on beach stranded *Rhodophyta* also positively correlated with coastal chlorophyll-*a* concentration. In other words, beach-cast assemblages of *Rhodophyta* tend to include more turbidity specialists in eutrophic contexts. This finding complies with the high taxonomic richness and variable tolerance to turbidity which is expected to drive further community changes in *Rhodophyta* (Gallon et al., 2014). Overall, our results suggest that the sensitivity of our beach wrack CTTI to coastal eutrophication is mainly driven by *Rhodophyta* communities.

4.2. CTL decreases with eutrophication

Eutrophication also contributes to the global decline of kelp forests habitats and associated services (Krumhansl et al., 2016). This decline appears beneficial to opportunistic turf algal communities which are functionally different as they provide little to no three-dimensional structure to coastal seascapes (Filbee-Dexter and Wernberg, 2018). Our CTL index was designed to track such a community functional shift as a response to coastal eutrophication along Brittany's coasts. Calculated from the whole beach wrack macroalgae community, it varied negatively with coastal chlorophyll-*a* concentration as expected.

4.3. Complementary metrics to the broader WFD ecological indicator

We finally explored how our beach wrack macroalgae community metrics covaried with the ecological indicators computed within the WFD framework. We found the expected pattern: low values of Community Tolerance to Turbidity Index were more related to the very good state of Good Ecological Status, the indicator which encompasses the monitoring of biological, physico-chemical and hydromorphological features of coastal waters. Although we did not detect a strong significant relationship between our community weighted thallus length and GES, we observed a slight non significant trend to find species with longer thallus in beaches with very good state of GES (the expected pattern). This is promising considering that our CTTI and CTL are continuous metrics computed at the beach scale whereas the WFD indicator is a discrete metric computed at the spatial resolution of 102 km^2 areas on average (European Environment Agency (EEA) (EEA) 2018). Several challenges have been identified toward the improvement of surface waters ecological indicators within the WFD framework (Reyjol et al., 2014). These include a better control of the uncertainty inherent to wide multicriteria ecological evaluations, and the development of size related functional metrics as complementary assessment tools. Our CTTI and CTL serve these objectives and may provide insightful assessment toward a broad monitoring of coastal eutrophication.

4.4. Limits and ways forward

Our intent was to take advantage of macroalgae fragments included in beach-cast material (Orr et al., 2005) to infer changes in benthic macroalgae communities as a response to coastal eutrophication (Scanlan et al., 2007). This approach relies on a compromise between i) a greater need for approximated proxies in place of direct observations, and ii) an increased monitoring capability. First, we sampled macroalgae in beach wracks, which have been shown correlated with the diversity of proximate coastal habitats (Suursaar et al., 2014; Thibault et al., 2022). Then, our attempt at creating community-wide indicators from taxa specific functional traits was challenged by the availability of such trait values in regional databases. Indeed, we were able to collect maximum thallus length values for 80 % of beach-cast taxa, but 65 % only for the turbidity tolerance trait in the European AlgaeTraits Database (Vranken et al., 2023). Further completion of this database will provide a powerful reference for large scale functional assessment of coastal ecosystem health (Reyjol et al., 2014). Remote sensing chlorophyll-*a* data also reflects the compromise between the spatiotemporal extent and the resolution of collected data (Maúre et al., 2021). The computation of the CTTI also rely on both sampling and methodological choices that may affect its precision as a community-wise indicateur of eutrophication. Further improvement may add weight to the presence/absence of some genera that are known as specialists of either eutrophic or oligotrophic conditions. Including the relative biomass of taxonomic subgroups may also improve the representation of phenomenons like *Chlorophyta* blooms as a response to pollution events.

On the other hand, these limits were counterbalanced by a substantial increase of the monitoring capability as well as the relative performance of the CTTI with respect to the study hypotheses. We were allowed to collect both macroalgae community and coastal water features data for two hundred beaches all around the coast of Brittany in a few months while computing the GES assessments for the Loire-Bretagne region hardly rely on 20 stations yearly. The beach wrack derived assessment thereby lowers the risk of spatio-temporal biases and increases the sample size. From a research perspective, such an extensive monitoring allows for exploring novel questions related to the ecology of the land sea continuum (Thibault et al., 2022), to coastal biogeography (Verniest et al., 2025) or impacts from global changes on coastal ecosystems. Trait value gathering opportunities offered by the AlgaeTraits database allowed for the computation of two functional community metrics which offered the advantage of being specific to the ecosystem state we aimed at monitoring. Altogether, this makes the whole study framework—from data collection to index computation—open and handy. This may constitute a strong advantage, as the implementation of either the WFD GES or the descriptors of the MSFD are currently limited by the required sampling effort that inherently limits the number of sampling stations and the area of targeted coastal water bodies (Bizzozero, 2020). Overall, our use of both biological and environmental proxies obviously comes with precision limits, which is compensated by the increased sample size, sampling resolution, cost and logistical effectiveness. Finally, such a monitoring holds a strong potential for citizen science programs by providing a mix of public awareness tools, managerial monitoring programs, and research materials (Chandler et al., 2017). The present study is linked to such a program, named "plages vivantes", that already offers training for individuals, educational sequences, the development of identification tools, and the centralization of data collected in a participatory manner.

5. Conclusion

Studying seaweed as well as all organic and inorganic debris deposited on the coastline could offer opportunities to monitor the state of coastal ecosystems indirectly and at lower cost. In line with recent studies illustrating the link between organic debris and marine habitats or environmental parameters, our study proposes two indicators of coastal water eutrophication. Our results show that community weighted indicators of functional traits related to the affinity to eutrophication correlate with seawater chlorophyll *a* concentration.

CRediT authorship contribution statement

M.T.: conceptualization, methodology, investigation, data curation, formal analysis, visualization, validation, writing—original draft, writing—review and editing; F.V.: investigation, methodology, validation, writing—review and editing; P.P.: data curation, writin-review and editing. V.V.: data curation. C.K.: conceptualization, methodology, investigation, funding acquisition, project administration, supervision, validation, writing – review and editing. I.LV. conceptualization, methodology, investigation, funding acquisition, project administration, supervision, validation, writing – review and editing.

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Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Pauline Poisson reports financial support was provided by Crédit Agricole SA. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gecco.2025.e03919.

Data availability

Data will be made available on request.

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