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Identifying vulnerable marine ecosystems: an image-based vulnerability index for the Southern Ocean seafloor

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A significant proportion of Southern Ocean seafloor biodiversity is thought to be associated with fragile, slow growing, long-lived, and habitat-forming taxa. Minimizing adverse impact to these so-called vulnerable marine ecosystems (VMEs) is a conservation priority that is often managed by relying on fisheries bycatch data, combined with threshold-based conservation rules in which all "indicator" taxa are considered equal. However, VME indicator taxa have different vulnerabilities to fishing disturbance and more consideration needs to be given to how these taxa may combine to form components of ecosystems with high conservation value. Here, we propose a multi-criteria approach to VME identification that explicitly considers multiple taxa identified from imagery as VME indicator morpho-taxa. Each VME indicator morpho-taxon is weighted differently, based on its vulnerability to fishing. Using the "Antarctic Seafloor Annotated Imagery Database", where 53 VME indicator morpho-taxa were manually annotated generating >40000 annotations, we computed an index of cumulative abundance and overall richness and assigned it to spatial grid cells. Our analysis quantifies the assemblage-level vulnerability to fishing, and allows assemblages to be characterized, e.g. as highly diverse or highly abundant. The implementation of this quantitative method is intended to enhance VME identification and contextualize the bycatch events.

Keywords: CCAMLR, deep sea, deep-sea fisheries, multi-criteria assessment, VME.

Introduction

The deep sea (<200 m depth) is considered as one of the most diverse and largest ecosystems on Earth (Robison, 2009; Ramirez-Llodra *et al.*, 2010; Clark *et al.*, 2016b), hosting unique and fragile communities and playing a key role in the ocean services used by humans (Jobstvogt *et al.*, 2014; Thurber *et al.*, 2014; Levin and Bris, 2015). The deep-sea benthos is impacted by direct and indirect fisheries disturbances (Clark and Rowden, 2009; Moore and Squires, 2016; Clark *et al.*, 2016a), such as the killing of non-target benthic animals, ploughing of the seabed and the resuspension of sediments, which can smother fauna (Palanques *et al.*, 2001; Mangi *et al.*, 2016; Clark *et al.*, 2016a). Recognizing the growing threat to deep-sea ecosystems, the United Nations General Assembly (UNGA) called upon member states and regional fisheries management organizations and arrangements (RFMO/As) to identify areas beyond national jurisdiction (ABJN) where benthic vulnerable marine ecosystems (VMEs) occur or are likely to occur, in order to prevent significant adverse impacts from fishing practices (UNGA, 2006). VMEs are considered ecosystems of high conservation value because they are dominated by fragile, long-lived, and slow growing epibenthic organisms, which are likely to be permanently altered by a short-term or chronic disturbance (Morato *et al.*, 2006; Sissenwine and Mace, 2007; Bensch *et al.*, 2008; Williams *et al.*, 2010; Mangi *et al.*, 2016; Clark *et al.*, 2016a).

In response to the UNGA resolution 61/105, the Food and Agriculture Organization (FAO) developed a series of guidelines to assist with the identification of VMEs (FAO, 2009). These guidelines list five criteria for identifying VMEs based on the biological characteristics of the biota they contain (FAO, 2009, paras 42–46): (i) uniqueness or rarity, (ii) functional significance of the habitat, (iii) fragility, (iv) life-history traits of component species that make recovery difficult, and (v) structural complexity (see Table 1, left column). No generic quantitative definition of a VME has, however, been provided by the FAO because vulnerability is a continuum among species (i.e. not a binary characteristic of a species), and is relative both to the type and intensity of threat (e.g. pollution vs. physical disturbance), or to regional benthic biodiversity characteristics (Parker and Bowden, 2010; Auster *et al.*, 2011). Hence, regional fishery bodies have each developed their own VME definitions for their area of jurisdiction, as well as their own list of VME indicator taxa (CCAMLR, 2009a, 2013a), whose presence is necessary but not sufficient to identify a VME (Thompson *et al.*, 2016).

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Table 1. Comparison between FAO (2009) and CCAMLR (2009b) criteria (n = 5 and 7, respectively) for identifying VMEs based on their benthic fauna characteristics.

FAO criterion	CCAMLR definition	CCAMLR scores
Uniqueness or rarity	**Rare or unique populations:** Vulnerable taxa containing species that create dense, isolated populations.	**High**: Populations are isolated **Medium** or **Low**: Population patch size or frequency of occurrence increases
Functional significance of the habitat	**Habitat-forming:** Structural species within the VME […] create habitat that could be used by other organisms.	The relative degree to which organisms contribute to generating this habitat.
Structural complexity	**Habitat-forming:** See “Functional significance of the habitat”.	See “Functional significance of the habitat”.
Fragility	**Fragility:** The potential for damage or mortality resulting from physical disturbance from bottom fishing gear.	**Medium** or **High**: Tall, brittle, or otherwise easily damaged. **Low**: Organisms that are resistant due to their structure or behaviour.
Life-history traits of component species that make recovery difficult	**Longevity:** Estimate of maximum longevity for the members of the taxon.	**High**: >30 years **Medium**: 10–30 years **Low**: <10 years
	Slow growth: Organisms which grow slowly will take a longer time to attain a large size or reproductive maturity.	**Medium** and **High**: Slow growth rates **Low**: Fast growth rates
	Larval dispersal potential: The range of dispersal by larvae and propagules influences the ability of a species to recolonize impacted areas.	**High**: Brooding species **Medium**: Mix of brooding species and broadcast spawners **Low**: Broadcast spawners
	Lack of adult motility: Does add some degree of vulnerability and decreases resilience because as adults those organisms cannot redistribute themselves in response to a direct disturbance, adjust their position if altered in some way, or move into a disturbed area to recolonize.	**High**: Sessile **Medium**: Limited potential for movement **Low**: Mobile

Vulnerable marine ecosystems in the Southern Ocean

Due to the remoteness and challenging environment of the Southern Ocean, data on benthic marine ecosystems are relatively limited and their distribution remains poorly understood (Reid, 2011). Recent discoveries are challenging our understanding of Antarctic benthic ecosystems and are further highlighting that we are still learning about them (Griffiths *et al.*, 2021). Southern Ocean benthic marine ecosystems, however, are characterized by high species endemism (Clarke and Johnston, 2003), and species with relatively slow growth rates compared with more temperate regions (Parker and Bowden, 2010). This makes them particularly at risk to direct human exploitation and anthropogenically induced climate change because of their relatively long recovery time [~10 years in the shallows, likely longer in deeper water, see (Zwerschke *et al.*, 2021)]. Functionally, adverse impacts on VME result in the loss of complex habitat formations (Clark *et al.*, 2016a), which are characterized by a high trophic and functional diversity, provide food and shelters for associated mobile fauna, and locally smooth the hydrodynamic patterns (Gutt *et al.*, 2017; Maldonado *et al.*, 2017).

The Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR) is the RFMO/A responsible for the protection of VMEs within its convention area in the Southern Ocean and committed to follow an ecosystem-based management approach (CCAMLR'P, 1980; Fabra and Gascón, 2008). To protect VMEs from bottom fishing impact, CCAMLR restricted bottom trawling to certain areas (CCAMLR, 2008), and bottom fishing with longlines or pots in depths shallower than 550 m (CCAMLR, 2013b). To identify a VME, CCAMLR tailored the five FAO criteria to its high seas realm and included consideration of motility and larval dispersal (see Table 1, middle column) (CCAMLR, 2009b). Mobile organisms have been considered by CCAMLR because some mobile animals: (i) may constitute habitat for others, e.g. dense populations of anemones (Tissot *et al.*, 2006), and (ii) have a high catchability, which makes them effective indicators (Parker and Bowden, 2010). By assigning a vulnerability score to the Antarctic benthic taxa and ranking them according to this score (see Table 1, right column), 23 benthic taxa have been identified as relevant VME indicator taxa in the Southern Ocean, see (CCAMLR, 2009a). However, CCAMLR considers the 23 VME indicator taxa equally vulnerable to fishing during the subsequent VME identification processes.

Based on the presence of VME indicator taxa, 53 areas in the Southern Ocean have been registered so far as supporting VMEs and accordingly are permanently closed to bottom fishing. Collectively, however, these cover <0.01% of the CCAMLR's convention area (<3000 km^2 of the 35716100 km^2). Registered VMEs are in relatively shallow waters (average: 225 m), are mostly concentrated in the South Atlantic Ocean ($n = 42$, i.e. 79% of total, subareas 48.1 and 48.2), and are protected (CCAMLR, 2009b). Although bottom fishing is prohibited in subarea 48.1, CCAMLR continues to assign new VMEs sites in this subarea, which is under severe threat of climate change (Lockhart and Hocevar, 2021). CCAMLR also imposes temporal spatial closures to fishing in “VME Risk Areas” ($n = 78$, average depth: 1150 m), which are 1 nm radius areas around locations of where a VME indicator taxon was encountered above a certain threshold (CCAMLR, 2013b).

Limitations of existing VME protection in the Southern Ocean

Unlike some RFMO/As that have adopted VME closure areas based only on marine features, e.g. seamounts (Ardron *et al.*, 2014; Wright *et al.*, 2015; Watling and Auster, 2017), CCAMLR mainly relies on observer records of incidental

VME taxon catch during fishing operations. Longline fishing is the predominant fishing method in the CCAMLR area and VME taxa have very different catchabilities by this gear, when compared with trawls (Sharp *et al.*, 2009; CCAMLR, 2013a). Catch of an indicator taxon, above a threshold amount, e.g. 10 kg of VME indicator taxa on a single line segment (CCAMLR, 2013b), triggers a temporary spatial closure of one nautical mile radius, and the declaration of a "VME Risk Area" (CCAMLR, 2013b). This approach is problematic because (i) relying on incidental catch of benthic taxa implies a sampling bias towards areas with active bottom fishing, (ii) fishing gear has very limited ability to sample VME indicator taxa (Auster *et al.*, 2011; Thompson *et al.*, 2016; Brasier *et al.*, 2018), and (iii) selectivity and catchability varies across taxa due to differences in morphology, ecology, and life history (Parker and Bowden, 2010). Also, since the CCAMLR threshold-based protection measures are not taxon specific, this results in an incomplete assessment of vulnerability (Lockhart and Hocevar, 2021). However, in recent years, an increasing number of VMEs were designated based on research benthic data from scientific surveys, e.g. (Lockhart and Hocevar, 2021). Similar to most RFMO/As, CCAMLR's VME indicator taxa list mainly uses very coarse taxonomic groups. This is because the life-history of many species is poorly known and identification is conducted on board by fisheries observers, while several groups are reliant on taxonomic experts for species-level identification (Parker and Bowden, 2010; Auster *et al.*, 2011). Moreover, no quantitative definition of a VME has been provided for the Southern Ocean (Jones and Lockhart, 2011), leaving vulnerability as a relative term, and influenced by the subjectivity of experts. Given the limitations of fishery by-catch data, alternative methods are required for identifying and quantifying VME. The lack of indicative and ecologically meaningful numerical metrics leads to inconsistency and, at times, a lack of transparency in the VME identification process (Burgman *et al.*, 2011; Martin *et al.*, 2012).

Related work

Repeatable and reproducible quantitative methods can facilitate standardizing robust impact assessments and routine monitoring for VMEs (Penney and Guinotte, 2013; Ardron *et al.*, 2014). However, these methods have not yet been applied in the Southern Ocean (Bell *et al.*, 2019). Morato *et al.* (2018) recently proposed a multi-criteria VME assessment in the North Atlantic area, which captures the fact that not all VME have the same vulnerability to human activities. Their spatial assessment aggregated data by weighting each record of VME indicator taxon differently, based on its vulnerability in regards to the five FAO criteria (Morato *et al.*, 2018). The resulting grid map quantified the community's vulnerability to fishing within a single metric, termed the "VME index". This "VME index" grid map of the North Atlantic Ocean basin has been made publicly available and can inform relevant stakeholders about where vulnerable benthic communities have been detected (Morato *et al.*, 2021). The VME index was only quantified for locations where fishing bycatch or scientific records data were available (Morato *et al.*, 2021). In contrast, Burgos *et al.* (2020) used species distribution modelling in order to map a VME index over vast areas, which identified target areas for further exploration and conservation efforts. These studies used only abundance data of VME indicator taxa, but recent work near the Antarctic Peninsula (Lockhart and Hocevar, 2021) has highlighted the importance of considering both abundance and diversity of the VME indicator taxa to ensure the protection of richly diverse and vulnerable communities.

Objectives

The objectives of this study are to:

a. Define a vulnerability based on criteria defined by CCAMLR.
b. Quantify and map the vulnerability of benthic assemblages to fishing, while accounting for both indicator taxa richness and abundance, measured from underwater imagery data.
c. Categorize areas depending on their conservation value in terms of abundance and/or richness of vulnerable species.

Material and methods

Dataset

One thousand eight hundred images, part of the Antarctic Seafloor Annotated Imagery Database (AS-AID) dataset, were annotated for the presence and abundance of VME indicator morpho-taxa (Jansen *et al.*, 2023). Figure 1 shows the spatial distribution of the data around Antarctica, and its bathymetric distribution in Appendix 1. The dataset comprises >40000 manual annotations of 53 VME indicator morpho-taxa (combining both morphological and taxonomic information). Annotations were generally performed using the BIIGLE 2.0 platform (Langenkämper *et al.*, 2017), but some colonial taxa (Bryozoans, Poriferans, Hydrocorals, and Hydroids) for which individual colonies could not be distinguished reliably, were quantified using a grid of 108 evenly spaced points over the images using CoralNet (Beijbom, 2015). We used a 9 × 12 points grid (i.e. 108 points) for all images to best match the 3 × 4 height–to–width ratio and considered 108 points to be a good compromise between sampling effort and time constraint. A single scorer (CG) annotated all images, subsequently reviewed by an independent scorer (JJ). The VME morpho-taxon categories are based on both morphological and taxonomic information. Morphological classes were defined based on the CATAMI classification scheme (Althaus *et al.*, 2015), e.g. "Octocorals_Bottle_Brush_Complex", and concatenated with the VME indicator taxon as defined by CCAMLR (CCAMLR, 2009a), e.g. "Alcyonacea-Octocorals_Bottle_Brush_Complex" and "Gorgonacea-Octocorals_Bottle_Brush_Complex" (Untiedt *et al.*, 2021). The rationale for using both schemas is to account for the growth form of an organism, which greatly impacts its vulnerability to human activity (CATAMI information), while being compatible with the list of VME indicator taxa that is already used by CCAMLR. Based on functional morphology traits, we used the CATAMI scheme because (i) it was developed for scoring underwater imagery where identification of species is often challenging due to several factors (e.g. imaging technology and quality aspects, the taxonomic knowledge of the region), and has been applied in (Ferrari *et al.*, 2018; Untiedt *et al.*, 2021), and (ii) the functional morphology descriptors (e.g. encrusting vs. large branching) it defines are useful to evaluate the organism's vulnerability to physical disturbance.

All annotated images were georeferenced using the projected coordinate system called "Antarctic Polar Stereo-

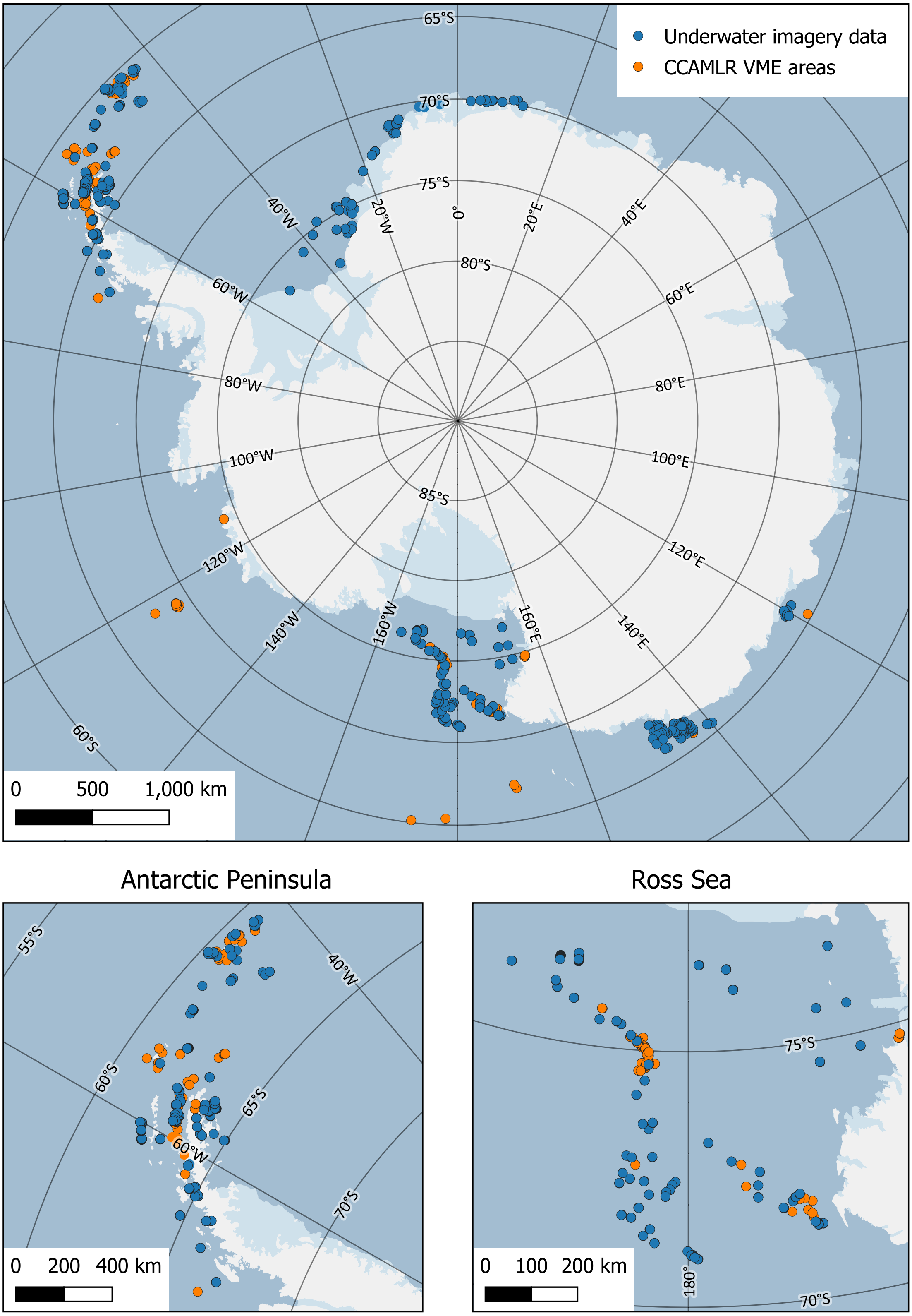

Figure 1. Spatial distribution of imagery data. Blue dots represent 500 × 500 m grid cell locations (n = 858) containing data included in this study. CCAMLR VME areas (9 February 2022, orange dots), land (white), ice shelf (light blue), and sea (blue) are indicated for reference. Bottom insets were added to zoom on the Antarctic Peninsula and the Ross Sea for visualization purposes, no quantitative comparison of these two regions was performed in this study. Base layers are from Quantartica3. Data were projected using the Antarctic Polar Stereographic system (EPSG: 3031, WGS: 84).

graphic” (WGS 84–EPSG:3031). An isotropic grid (500 × 500 m) was used in this coordinate system as reference for the analysis. For each grid cell where data were available, the percentage cover of each VME morphotaxon was calculated, and used as a measure of abundance. For data collected on CoralNet, the abundance was computed by considering the number of points labelled as a given VME morpho-taxon divided by the total number of labelled points ($n = 108$). For data collected on BIIGLE, where each organism was labelled individually, the abundance was derived from the percentage cover of each VME morpho-taxon category. The dataset of raw percentage cover used in this study, along with the scoring guide, which was used to ensure consistent annotations across the imagery, is publicly available as part of an open-source data repository (osf.io/4n3bp/).

Methods

This section presents the methodology used to quantify the vulnerability of benthic assemblages in the Southern Ocean using a multi-criteria scoring process to calculate a vulnerability index score. It is based on the work of (Ardron *et al.*, 2014; Morato *et al.*, 2018), recently applied to data of “presence-only” VME indicator taxa samples in the North Atlantic basin (Morato *et al.*, 2021). The current work extends this work to include VME indicator morpho-taxa abundance data acquired from underwater imagery collected in the Southern Ocean. The vulnerability definition is based on the CCAMLR guidelines (CCAMLR, 2009b), which focus on the threat of fishing to benthic ecosystems.

Our method is based on spatially gridded data, where multiple images contribute to the assessment of a single 500 × 500 m grid cell. Because only a small portion of each grid cell was sampled, the spatial extent of VMEs may not be captured fully, as has been suggested by Watling and Auster (2021). Instead, this study will assess the vulnerability of marine benthic assemblages (vs. ecosystems). For each grid cell, three values are calculated

(i) an “abundance-based VME index”, which accounts for the cumulative abundance of VME indicator morpho-taxa in each 500 × 500 m grid cell.
(ii) a “richness-based VME index”, which accounts for the richness of VME indicator morpho-taxa in each 500 × 500 m grid cell.
(iii) a “confidence index”, which estimates the confidence associated with the raw data used to calculate the above mentioned VME indices.

Assigning a vulnerability score to VME indicator morpho-taxa

CCAMLR VME indicator taxa have a range of vulnerabilities to fishing impacts (CCAMLR, 2009b) and thus should be weighted differently when aggregated to assess the overall vulnerability of the benthic assemblage. CCAMLR (2009b) provided a score (low, medium, or high) for each CCAMLR VME indicator taxon based on seven CCAMLR vulnerability criteria (see Table 1). However, the taxonomic resolution used by CCAMLR is typically coarse and there is, therefore, a large range in the vulnerability of organisms captured within a single CCAMLR grouping. To address this, we considered morphology in our classification of VME indicator taxa. The growth form of an organism greatly impacts its vulnerability to human activities, for example, large, erect, and complex, branching morphologies are expected to be more vulnerable to bottom impacts than encrusting organisms with low relief. Morpho-types of a given taxon were initially assigned their CCAMLR scores (low (1), medium (2), or high (3), see Table 1), which were then refined to account for their specific morphology by Southern Ocean taxonomic experts. To compute an overall vulnerability score, the CCAMLR criteria were weighted differently because of the high correlation between some of them. The criteria “Slow growth” and “Longevity” are typically highly correlated and so they were combined into a single “Life history” value, as recommended by Ardron *et al.* (2014). Since the “Life history” criterion can be considered as uncorrelated with the other CCAMLR criteria, the vulnerability score of each VME indicator taxon aggregates all six criteria using the quadratic mean, following Burgos *et al.* (2020) and Morato *et al.* (2018).

Mapping the abundance-based VME index

The abundance of each VME indicator morpho-taxon is assigned to each 500 × 500 m grid cell by computing its percentage cover across all images georeferenced inside it (see Section 2.1). The “abundance-based VME index” is calculated from the abundance of each morpho-taxon modulated by its vulnerability score, see Figure 2. For each 500 × 500 m grid cell, the abundance of each VME indicator morpho-taxon is multiplied by its vulnerability score. The abundance-based VME index of each 500 × 500 m grid cell is then computed by summing the vulnerability-weighted abundance values of all VME indicator morpho-taxa. Consequently, a high VME abundance index indicates locations where there is a higher weighted-abundance of vulnerable morpho-taxa.

Mapping the richness-based VME index

The richness of VME indicator morpho-taxa is assigned to each 500 × 500 m grid cell by counting their number across all images georeferenced inside it. The “richness-based VME index” is calculated from the presence of each morpho-taxon modulated by its vulnerability score, see Figure 3. For each 500 × 500 m grid cell, the “presence-absence” data of each VME indicator morpho-taxon (1 if detected, 0 otherwise) is multiplied by its vulnerability score. A measure of the assemblage richness is then computed by summing the vulnerability-weighted presence values of all VME indicator morpho-taxa. Because the sampling effort varies across grid cells, the richness-based measure S is standardized by the sampled area A within each 500 × 500 m cell, using the following equation (Zintzen *et al.*, 2011):

$$\text{Standardized richness} = \frac{\ln(S)}{\ln(A)}. \tag{1}$$

As a result, a high richness-based VME index indicates locations where there is a relatively higher richness of vulnerable morpho-taxa.

Mapping a confidence index

A confidence index was calculated for each 500 × 500 m grid cell in order to account for the varying intensity of sampling, quality of the image, and the amount of time that has passed since the image was collected. For each 500 × 500 m grid cell, this confidence index was based on three criteria: (i) the sampling effort within the grid cell, (ii) the average image quality, and (iii) the average age of the images contained in the grid cell. The sampling effort was computed as the percentage of a

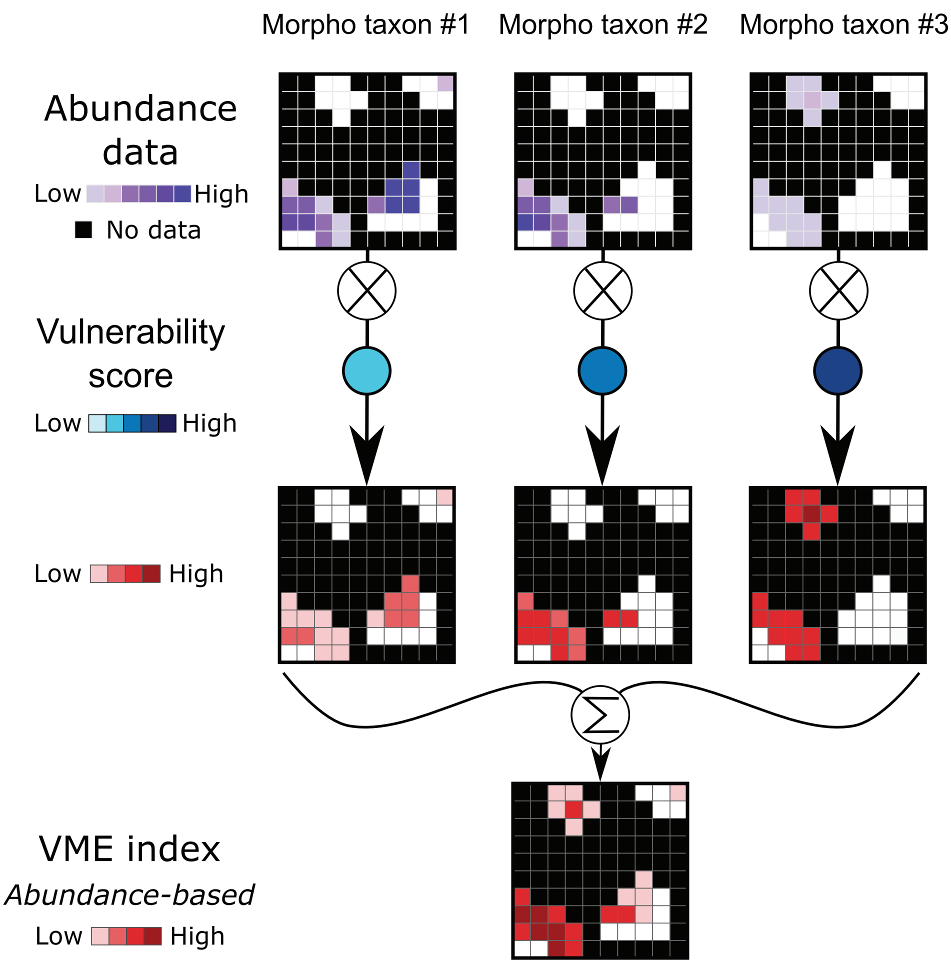

Figure 2. VME index, abundance-based, calculation method. Theoretical scenario in a 5000 × 5000 m area containing 100 cells that each measure 500 × 500 m. Black 500 × 500 m grid cells indicate cells for which there was no image available. White grid cells indicate that the VME morpho-taxon was not detected. When data were available (i.e. cell not black), multiple images contributed to the abundance measure assigned to a given 500 × 500 m grid cell. The calculation steps are, from top to bottom: (i) Multiplying the abundance data of each VME morpho-taxon by its vulnerability score, and (ii) Summing the results of the previous step across all VME morpho-taxa. Black grid cells indicate grid cells for which there are no data, while white grid cells indicate that the VME morpho-taxon was not detected.

500 × 500 m grid cell area that has been imaged and scored. The image quality was computed using the BRISQUE algorithm (Mittal *et al.*, 2012) with the Python package image-quality (version 1.2.7), and averaged across the images contained within a grid cell. The image age was derived from the year when the imagery survey was conducted compared to 2022, expressed in negative values (e.g. −3 for a 2019 survey). For each criterion, a relative score was assigned (low, medium, and high, scored as 1, 2, and 3, respectively) using the Jenks natural breaks classification method (Jenks, 1967), as detailed in Table 2. The confidence index was obtained by summing the three scores for each 500 × 500 m grid cell. The confidence index ranges from 3 to 9. A grid cell with a confidence index of 9 indicates a high confidence in the underlying data. Confidence index data could not be computed for six grid cells due to missing data (<1% of the cells, $n_{tot} = 858$).

Code and data availability

Python (version 3.8) was used for the analysis, QGIS (version 3.20.1), and Quantarctica (version 3) (Matsuoka *et al.*, 2021) for the visualization of results. To enhance the reproducibility of the study, all the code base has been made publicly available on a Github repository (github.com/charleygros/so_vme_index). The Github documentation explains how the code base can be used by other researchers to perform similar analyses using different abundance data, different species, and/or vulnerability scores. The circumpolar raster layers containing the computed index values are also open source, hosted on an OSF repository (osf.io/4n3bp/), since the present manuscript only displays the results of a small area around the western Antarctic Peninsula (see case study shown on Figure 6).

Results

Morpho-taxa vulnerability score

Figure 4 shows the variability of the vulnerability score across CATAMI morphologies, for 12 VME indicator morpho-taxa covering six taxonomic groups with two morphologies per taxon. The vulnerability score for all VME morpho-taxa ($n = 68$) can be found in Appendix 2, as well as on the OSF repository (see Section 2.2.5). Considering taxonomic classification, "Gorgonacea" was the most vulnerable taxon, while "Ascidiacea" was the least vulnerable (see e.g. on Figure 4). Within a taxonomic group, the vulnerability scores often

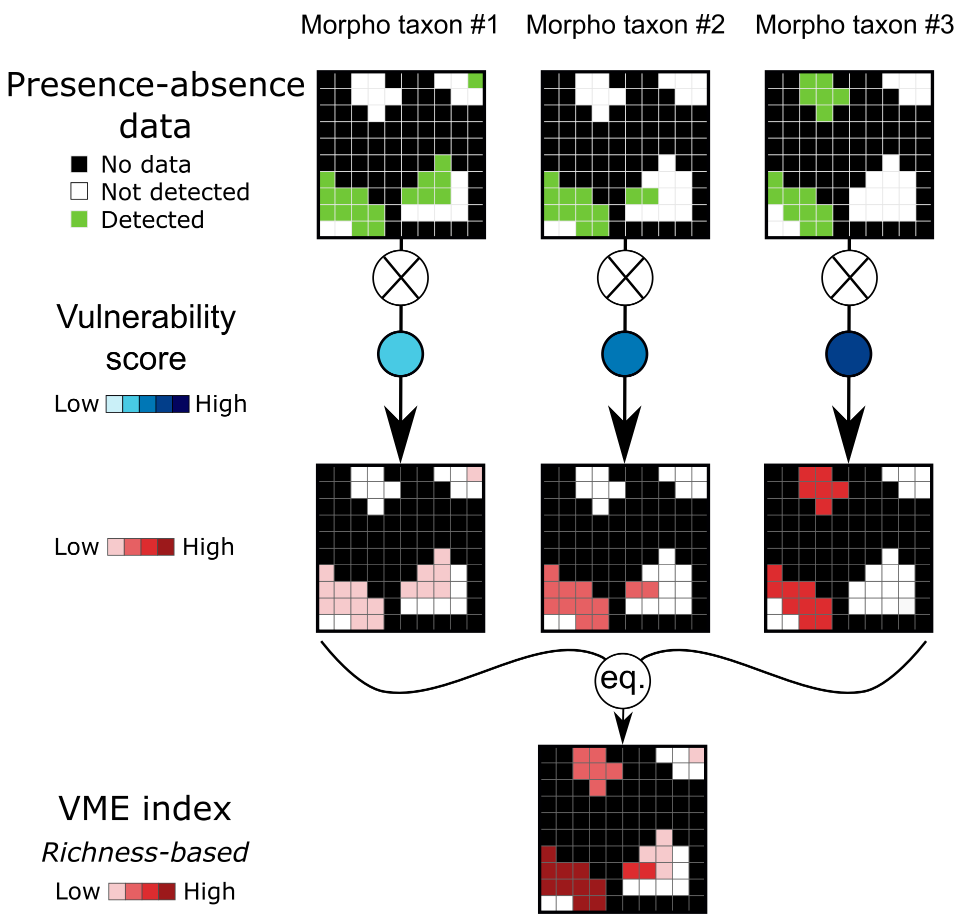

Figure 3. VME index, richness-based, calculation method. Theoretical scenario in a 5000 × 5000 m area, split into a 10 × 10 grid, each cell being 500 × 500 m. Black 500 × 500 m grid cells indicate cells for which there was no image available. White grid cells indicate that the VME morpho-taxon was not detected. When data were available (i.e. cell not black), multiple images contributed to the richness measure assigned to a given 500 × 500 m grid cell. The calculation steps are, from top to bottom: (i) Multiplying the "presence-absence" data of each VME morpho-taxon by its vulnerability score, and (ii) Summing the results of the previous step across all VME morpho-taxa to get the richness in each cell, then standardize it to account for varying sampling effort (see Equation 1 in text).

Table 2. Criteria used to score the different components of the confidence index.

Criteria	Low confidence score = 1	Medium confidence score = 2	High confidence score = 3
Sampling effort inside a grid cell	<750 m^2	≥ 750 and $\leq 2\,000$ m^2	$>2\,000$ m^2
Image quality	<4	≥ 4 and ≤ 31	>31
Image age	>14 years	≥ 4 and ≤ 14 years	<4 years

The three categories (low, medium, and high) were obtained using the Jenks natural breaks classification method (Jenks, 1967).

varied with morphology, for example in "Bryozoa" with a *SD* of 0.27 among the vulnerability of six morphologies. Conversely, the same vulnerability score was assigned to all three "Pennatulacea" morpho-types, because these animals have a similar morphology (long quills or whips with a head of polyps) and lifestyle. "Porifera-Erect 3D-branching" had a higher vulnerability score than "Porifera-Crust-encrusting", mainly because their morphology makes them more susceptible to fishing gear, while encrusting growth forms are comparatively more resilient to damage due to their low relief and are known to include fast growing species (Schönberg, 2021). "Ascidiacea-Stalked-solitary" and "Unstalked-colonial" had similar vulnerability scores, except for the "Fragility" criterion where the solitary, stalked morphotype was more easily damaged by fishing activities than its colonial, unstalked counterpart.

Distribution of VME indices' values

The correlation between the abundance- and richness-based VME indices across cells was moderate (Pearson correlation $r = 0.52$, $p < 0.05$), which is also illustrated by their different distributions shown on Figure 5. These differences reinforce the importance of considering both indices. The two VME indices also had different ranges of values: from 0 to 173.33 for the abundance-based index vs. from 0 to 2.12 for the richness-based index. Forty-five cells (i.e. 5.2% of the sampled area) had a VME index value of zero since no VME indicator morpho-taxon was detected in these cells. For the

(a)

	Habitat forming	Rare or unique	Fragility	Life history	Larval dispersal	Sessility	**Vulnerability Score**
Bryozoans Hard branching	2	3	3	2.5	2	3	**2.62**
Bryozoans Soft foliaceous	2	3	1	1	2	3	**2.16**

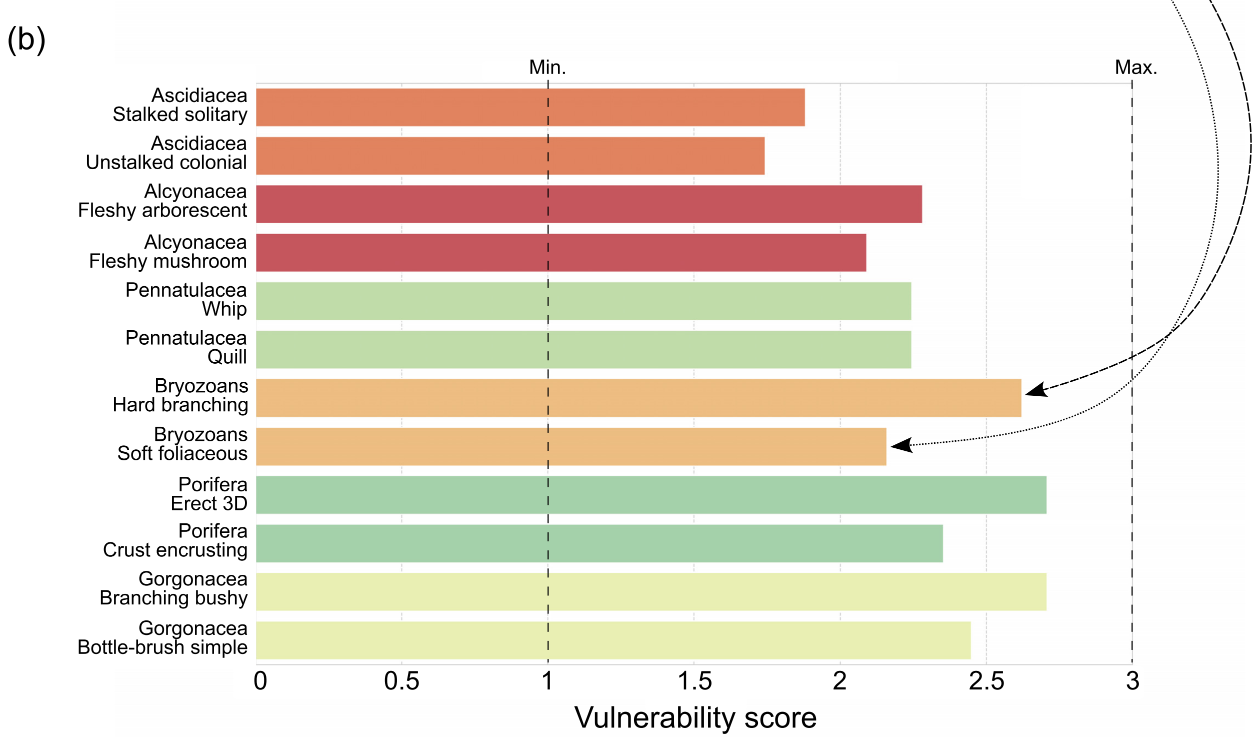

Figure 4. Examples of vulnerability scores of VME indicator morpho-taxa. Top panel shows how the vulnerability scores are computed for two VME morpho-taxa. The vulnerability score combines the ratings (between 1 and 3) of the seven CCAMLR criteria. Bottom panel displays the resulting vulnerability scores of 12 VME indicator morpho-taxa. Scores can range from a minimum of 1 to a maximum of 3. The morpho-taxa are coloured according to the taxonomic group.

sake of clarity, both indices were categorized into two levels (low vs. high) using the Jenks natural breaks classification method (Jenks, 1967). For each index, the break values are indicated with black plain vertical bars on Figure 5, e.g. 37.08 for the abundance-based VME index. These levels were used to categorize the grid cells based on both VME indices: (i) cells with a low level of both abundance- and richness-based indices (54.89%), (ii) cells with a high level of both abundance- and richness-based indices (8.8%), (iii) cells with a high level of abundance-based index and a low level of richness-based index (3.1%), and (iv) cells with a low level of abundance-based index and a high level of richness-based index (33.21%).

In our dataset, the confidence index values ranged from four to nine, see Figure 5. Data acquired in grid cells with a confidence index of nine reached the highest score for each of the three criteria (see criteria of Table 2). The confidence index values were categorised in three levels (low vs. medium vs. high) using the Jenks natural breaks classification method (Jenks, 1967). The distribution of the confidence levels across cells was the following: 50.12% of low confidence level, 40.73% medium, and 9.15% high.

Twenty-four out of the 858 grid-cells (2.8%) overlapped with areas registered as VME by CCAMLR. Two of them are in subarea 48.1 (near the Antarctic Peninsula), three in subarea 58.4.1 (D'Urville Sea), and 19 in subarea 88.1 (Ross Sea). These cells had an averaged abundance-based VME index of 22.09 ± 22.14, and a richness-based VME index of 0.67 ± 0.20, which averaged value corresponds to a low level for both VME indices.

Spatial distribution and qualitative assessment

This section presents the results of the benthic vulnerability quantification in a case study located on the western Antarctic Peninsula, see Figure 6. Most cells ($n = 27$, 93%) had a low level of abundance-based VME index (coloured in yellow or green cells on Figure 6). Cells at the top of the study area all have a high level of richness-based VME index (green or red cells on Figure 6).

A qualitative assessment of the VME index levels can be performed by examining the underlying imagery of the benthic assemblages. Images located in the "yellow" cells mainly showed soft substrate, with a low richness level of VME in-

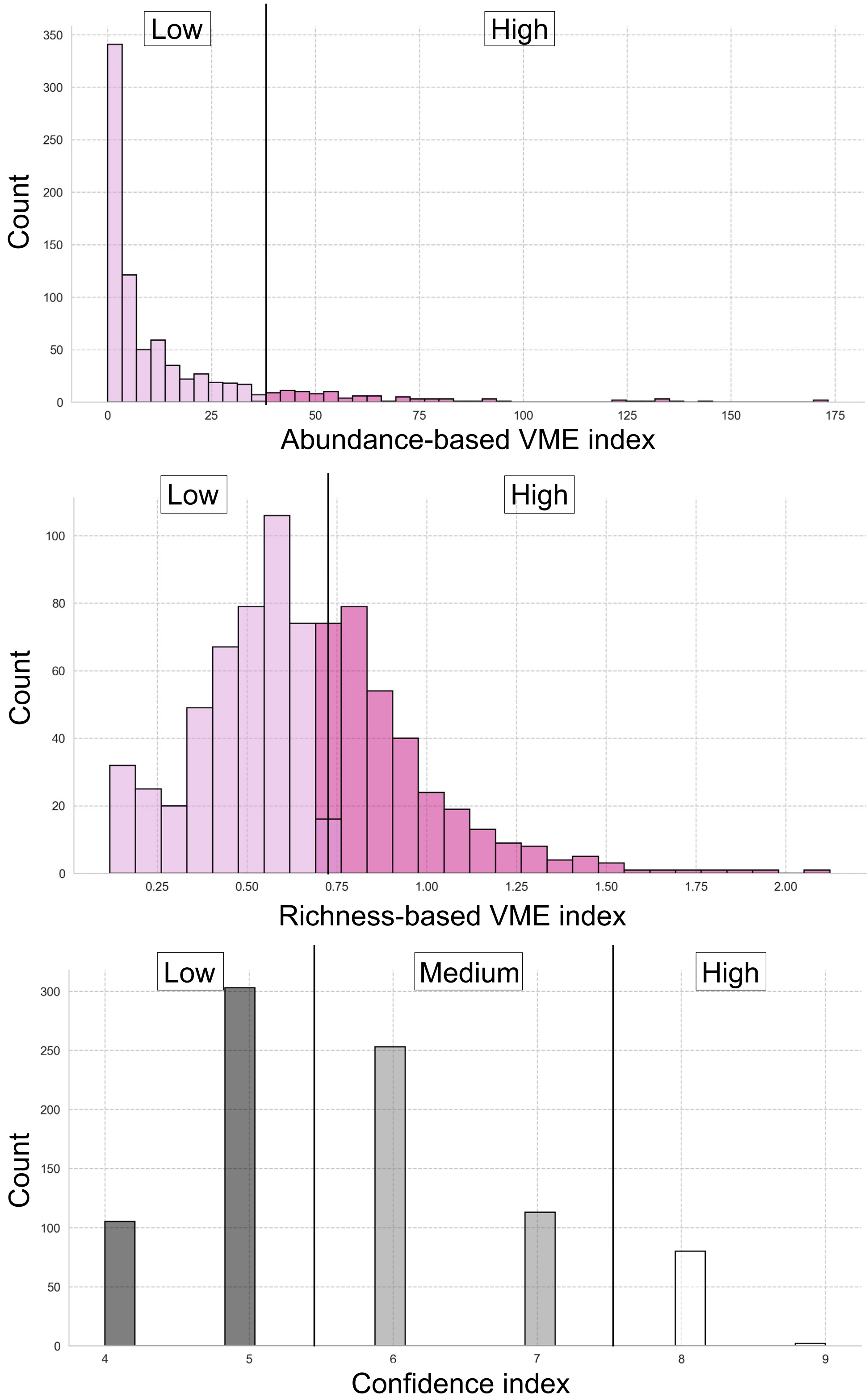

Figure 5. Distribution of the abundance-based VME index, richness-based VME index, and confidence index. Each bar plot represents the number of grid cells for different ranges of index values ($n_{tot} = 858$). The plain vertical lines represent the breaks used to categorize the indices into levels: low vs. high, or low vs. medium vs. high. The level thresholds were defined using the Jenks natural breaks classification method (Jenks, 1967).

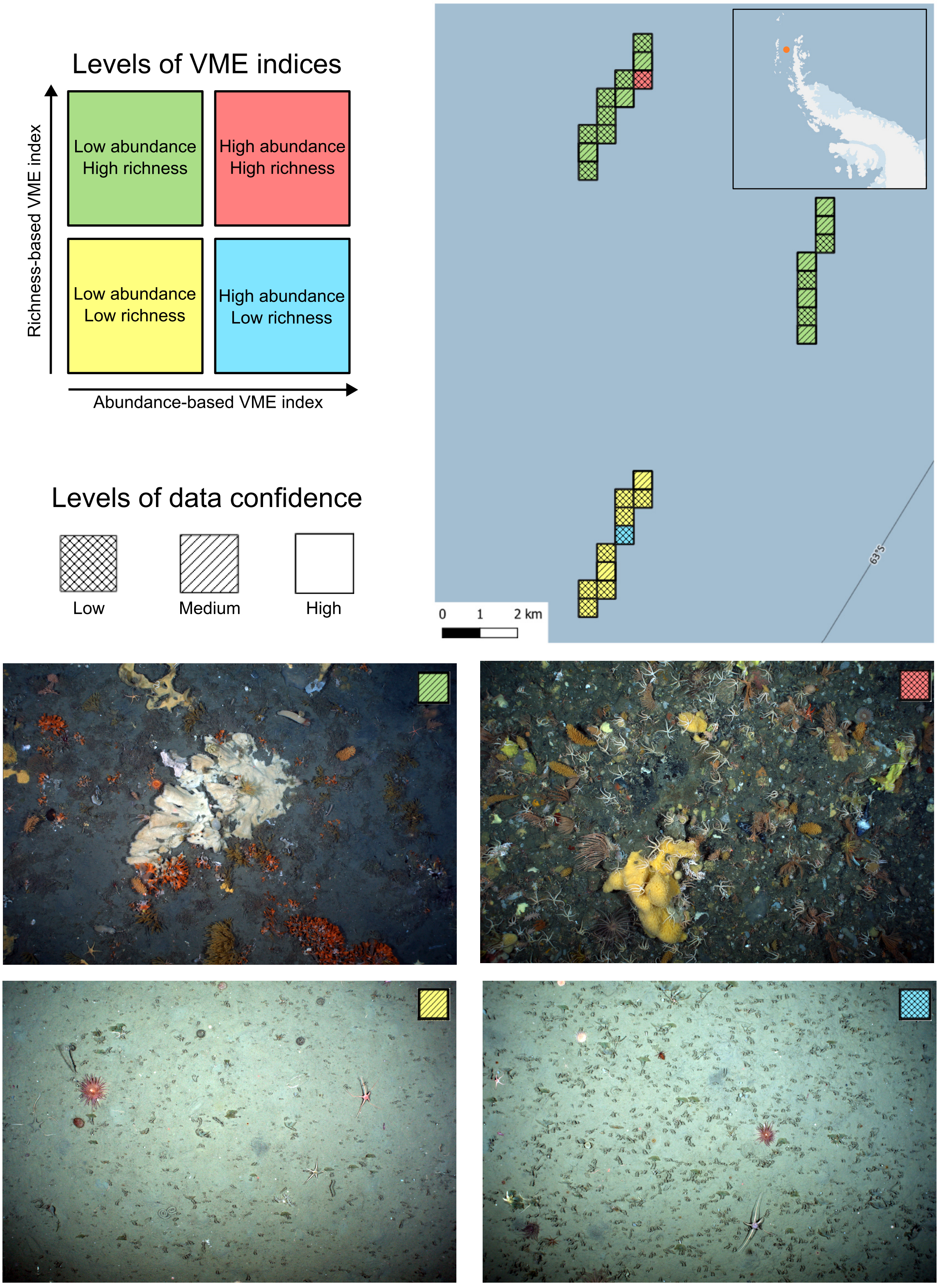

Figure 6. Case study—qualitative assessment of the spatial quantification of benthic vulnerability. The cells are colour coded based on the level of VME indices, and filled with a pattern based on the level of the underlying data confidence. Images were acquired in cells with the same colour code. Coordinates are using the Antarctic Polar Stereographic system (EPSG: 3031, WGS: 84).

dicator species (dominated by "Serpulidae-Polychaete") and a low abundance level of VME indicator species. Surrounded by "yellow" cells, there was a "blue" cell where the percentage cover of "Serpulidae-Polychaete" was high, inducing a high level of abundance-based VME index, while the richness-based index remained low. Conversely, the displayed images from the cells at the top of the study area showed a harder substrate and a greater richness of VME indicator species ("green" or "red" cells), with different morphologies of "Bryozoans", "Porifera", and "Octocorals". In addition to a high richness, the image from the "red" cell shows a higher coverage of the seafloor by VME indicator species, which can explain the high level of abundance- and richness-based VME indices.

Most cells in this area ($n = 19$, 66%) had a low level of data confidence index (diagonal grid pattern on Figure 6), mainly because of a low sampling effort (<750 m^2). In comparison, the remaining ten cells (34%) had a higher sampling effort (≥ 750 m^2), which contributed to a medium level of data confidence index (diagonal pattern on Figure 6).

Discussion

This study presents a method to quantify the vulnerability of benthic assemblages to physical disturbance in the Southern Ocean. The method is applied to VME indicator morpho-taxa abundance data derived from underwater-imagery. The results allow characterizing different levels of vulnerability to fishing across the surveyed areas, reflecting different levels of abundance and richness of vulnerable benthic assemblages. The method is reproducible and can be easily applied to other datasets and use other vulnerability criteria.

Index computation method

To summarize the vulnerability of benthic assemblages to fishing, the proposed method computes an abundance-based VME index from abundance data, and a richness-based VME index from "Presence-Absence" data. This work builds upon the work from Morato *et al.* (2018) in the North Atlantic Ocean. An important addition compared to Morato *et al.* (2018) is the consideration of the richness of VME indicator organisms, along with their overall abundance. This is the first time a quantitative index that explicitly captures and integrates the differential vulnerability of indicator morpho-taxa has been demonstrated and applied in the Southern Ocean. Qualitative assessment of varying levels of abundance and richness confirms the coherence and reliability of these indices.

A number of different ways of calculating the final indices were considered before deciding on the approach presented here. Preliminary analyses trialled summing the criterion scores for each individual morpho-taxa, instead of using the quadratic mean, see Section 2.2.1. However, as also noted by Ardron *et al.* (2014), the lack of information for some morpho-taxa means that the score for some criteria is missing, which prevents the use of the "summation" operator to compute the vulnerability score over all criteria. As for the data aggregation across morpho-taxa to obtain a single value summarizing the vulnerability of the assemblage, we used the "summation" operator to estimate the cumulative percentage cover of each VME indicator morpho-taxon, vulnerability-weighted, within each grid cell to compute the abundance-based VME index. Conversely, Morato *et al.* (2018) used the "maximum" operator to highlight areas with high abundance of vulnerable taxa, and Burgos *et al.* (2020) used the "average" operator to emphasize areas suitable for multiple VME indicator taxa. These differences in how to aggregate data raise the importance of clearly communicating the index meaning to the decision-makers. In our case, the abundance-based VME index should be interpreted as the cumulative abundance across VME morpho-taxa weighted by their vulnerability. Future studies may choose to alter the final aggregation operator to better fit their conservation priorities, like that discussed for the EBSA identification by Yamakita *et al.* (2017). In this study, images were spatially aggregated in a standardized 500 × 500 m grid. However, this grid-based spatial aggregation may be suboptimal for applications like identifying VME sites in situations where images are situated at the border between two grid cells. To accurately identify the location and size of VMEs, other aggregation methods should be investigated, like the "moving-window"-based method proposed by Williams *et al.* (2020) to estimate the size of VMEs, or other spatial clustering methods (Grubesic *et al.*, 2014), such as spatial autocorrelation approaches or the "scan-statistic" (Kulldorff *et al.*, 2003).

The interpretation of the current study results is hindered by the fact that the vast majority of the Southern Ocean has not been sampled. In areas where no observation is available, species distribution models could provide an effective means to infer VME indices from model predictions (Vierod *et al.*, 2014; Gros *et al.*, 2022).

Vulnerability criteria

This study proposes an extension of CCAMLR's vulnerability scoring for the listed VME indicator taxa by providing a vulnerability score to different morpho-types, acknowledging that morphology plays a role in an organism's vulnerability to physical disturbance. The morpho-types used in this study are part of the standardized and widely used CATAMI classification scheme (Althaus *et al.*, 2015). Although each of our morpho-taxa includes several families, it is however a step forward compared to the even broader categories originally used by CCAMLR. Future works could consider the addition of other morpho-types or taxa, e.g. CCAMLR only recognizes two classes of "Porifera" while two other classes are ignored. Besides, the CCAMLR vulnerability criteria (see Table 1) are strictly only really applicable to "species", whereas most benthic organisms cannot be resolved to species level, neither from underwater imagery nor during fishing operations. Future considerations should therefore focus on rethinking the species oriented CCAMLR vulnerability criteria, while conforming to CCAMLR precautionary approach.

From a gradient of vulnerability to priority site identification

The method presented in this article provides two continuous metrics of benthic assemblages' vulnerability to fishing. For the sake of clarity, these values were categorized into two levels of vulnerability, "Low" vs. "High". These vulnerability levels are a relative (not absolute) measure since thresholds delineating the levels were defined from the distribution of each index and will change when the dataset changes. Future studies should determine and validate how to reliably identify priority sites from the gradient of VME index values. The definition of cut-off values is a common challenge in site prioritization for protection and conservation efforts. In order to define what constitutes a "structurally complex habitat" (FAO VME criterion, see Table 1), Rowden *et al.* (2020) proposed a method to calculate density thresholds of a habitat forming VME indicator taxon based on the species richness associated with the habitat. Also, based on ground-truthed abundance data of a habitat-forming VME indicator taxon, Williams *et al.* (2020) presented a robust "spatial moving window" method to estimate the spatial extent of functional communities that can be considered as VME entities. Overall, an increase of ground-truth scientific validation is needed, which is currently lacking in the Southern Ocean where only 17% of the area closed to fishing because of VMEs have been mapped (Bell *et al.*, 2019). The present study was only possible thanks to the recently released AS-AID dataset (Jansen *et al.*, 2023), which set a precedent in biodiversity mapping in the Southern Ocean using underwater imagery. In addition, recent scientific surveys increased our knowledge of benthic communities in areas that are closed to fisheries (e.g. subareas 48.1 and 48.5) while being severely exposed to the risks associated with climate change (Friedlander *et al.*, 2020; Griffiths *et al.*, 2021; Lockhart and Hocevar, 2021). A better understanding of the Southern Ocean seafloor, and ultimately its protection, would largely benefit from additional imagery surveys, especially in locations with poor or no sampling effort.

Confidence index

Quantifying uncertainty is essential to properly inform decision-makers (Jansen *et al.*, 2022), especially in remote deep-sea ecosystems where high uncertainty is common. The use of underwater imagery data provides a better detectability of benthic organisms than by-catch data from fisheries, whose gear is not suited for benthic sampling (Jones and Lockhart, 2011). Further, the CCAMLR VME registry contains "VME risk area" locations that have been triggered by VME indicator taxa collected above a defined threshold (CCAMLR, 2009c). These encounter thresholds are not taxa-specific, have no consideration of species diversity, and have not been extensively validated (Parker *et al.*, 2009; Ardron *et al.*, 2014; Geange *et al.*, 2020; Lockhart and Hocevar, 2021), which implies uncertainties about their relevance and whether they are sufficient to guarantee a precautionary approach [as defined by CCAMLR (CCAMLR'P, 1980; Fabra and Gascón, 2008)]. Regarding underwater imagery data, the main limitation is its high cost, especially along slopes and abyssal plains of the Southern Ocean, which restricts its potential sampling effort, although there has been significant increase in both quality and quantity of deep-sea images in recent years (Bowden *et al.*, 2020; Cillari *et al.*, 2021; de Mendonça and Metaxas, 2021). Along with developing deep-sea imaging, it would be valuable to improve the operational sampling protocols implemented by fishing vessels in order to reduce the by-catch data uncertainty. As part of our proposed confidence index, the criterion called "age of the survey" has limitations since it is partly dependent on the longevity of organisms, which can vary widely among taxa. Besides the uncertainty associated with raw data, future studies could assign an uncertainty score to each taxon to account for different levels of knowledge about their vulnerability (e.g. vulnerability criteria, taxon life-history knowledge) or for their different detectability (e.g. catchability by a fishing gear, detectability by on-board scientific observers, or by imagery annotators, depending on the source of the data).

Perspectives

The present study emphasizes that vulnerability is a spectrum, which can and should be considered from different perspectives, e.g. abundance and richness of indicator species. Moreover, vulnerability is relative to a specific threat or set of threats, which may often interact to alter sensitivity to any one stressor. To be relevant for current management practices, this study focused on the threat of bottom fishing as part of the CCAMLR framework, while there is an increasing number of other threats for the Southern Ocean seafloor (Pan *et al.*, 2020; Goldsworthy and Brennan, 2021). To ignore the diversity of threats is likely to result in an insufficient and inadequate protection of VMEs (Friedlander *et al.*, 2020; Lockhart and Hocevar, 2021). Accounting for other threats would require a revision of the vulnerability criteria to quantify the benthic vulnerability, see Table 1. For instance, the CCAMLR criteria give only limited considerations to the issue that species that secrete aragonite are highly vulnerable to acidification. It could also be beneficial to review the relevance of the seven CCAMLR criteria to assess the vulnerability of seafloor communities, for example considering that in polar regions growth rate is not species specific (and certainly not morpho-taxon specific) but rather depends on local context (Fillinger *et al.*, 2013), e.g. food availability for suspension feeders ("Slow growth" criterion). An alternative set of criteria to assess vulnerability could include endemism, effective population size, stenothermy, skeleton type, successional stage, functional redundancy, and contribution to ecosystem services. All the above suggested improvements, e.g. use additional or different criteria to characterize vulnerability, can easily be implemented in the framework proposed in this study to generate a new mapping of VME indices.

Conclusion

Vulnerable hotspots of biodiversity in deep waters need urgent and comprehensive protection, not least because they can provide key ecosystem services, such as key mitigating feedback on climate change (Barnes *et al.*, 2018). Yet most of them in the Southern Ocean are probably yet to be discovered. Our study is an improvement from what is the status quo for defining VMEs in the Southern Ocean, which constitutes the first step towards efficient VME conservation. By considering differential vulnerability across indicator taxa and the importance of species richness, we are suggesting a practical alternative to the "blanket threshold for all VME taxa" used in fisheries management of the Southern Ocean. First of its kind to be tested in the Southern Ocean, this index-based method also provides a framework to derive ecologically meaningful metrics from image data, which could favour and encourage the use of imagery data in future applications. Potential applications of the VME indices include their use for risk assessment, such as for exploratory fisheries in places where image data are available. This work comes at a critical time where there is increased international focus on the sustainable use of oceans, and where data-based frameworks have an important role to play in properly informing decision-makers.

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Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Data availability statement

The data underlying this article are available in an OSF data repository at https://osf.io/4n3bp/, and can be accessed with the SHA-2 identifier 45e8907594c609f6e6d70c96228738b63948e8ed495e3f43adb17ef44b6a7178.

Author contribution

C.G.: conceptualization, investigation, formal analyses, and writing—original draft preparation; J.J.: ressources, writing—review and editing, and supervision; C.U.: conceptualization, investigation, and writing—review and editing; T.R.R.P., R.D., D.K.A.B., and D.A.B.: investigation, writing—review and editing; D.C.W.: writing—review and editing and supervision; and N.A.H.: conceptualization, writing—review and editing, and supervision.

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