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Anthropogenic pressure index for risk-based prioritisation of water-quality monitoring in an Amazonian estuary

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Abstract

Estuaries in the Amazon receive pressure from cities, ports, industry and land conversion, yet water-quality monitoring rarely follows where that pressure concentrates. We built a municipal Anthropogenic Pressure Index for the Estuary (APEI) for the 31 municipalities that share the Marajó Bay estuary (Pará, Brazil), from 18 public indicators in four pressure dimensions and one social vulnerability dimension. It is the first step of a monitoring screening and allocation protocol, not a water-quality model. Barcarena ranked first under four of five weighting schemes and all three aggregation methods (Spearman ρ with the equal-weight ranking from 0.922 to 0.994). In a joint uncertainty analysis that also varied data treatment and the indicator set (10,000 runs), Barcarena stayed in the top five in 86.6% of runs. Per unit area, the ranking changed more ($\rho = 0.789$) and three of the five leaders changed: the index reflects total load, not intensity. Three

weakly separated pressure profiles were identified: urban-industrial and port, land-use frontier, and riverine with a sanitation deficit. The 31 water-quality stations of the national water agency in operation are concentrated in seven municipalities. Four unmonitored municipalities combine high social vulnerability with robustly high pressure: Igarapé-Miri, Cametá, Portel and Breves. One new station in each would raise the share of people without adequate sewage in high-vulnerability municipalities who live where water quality is monitored from 2.8% to 56.4%, more than allocation by pressure or population alone. The procedure uses only public data and open code and is transferable to other data-poor estuaries.

Keywords: composite indicator; risk screening; decision support; social vulnerability; Marajó Bay; Monte Carlo sensitivity analysis

1 Introduction

Estuaries concentrate people, ports and industry, and they receive the combined load of what happens upstream. Human pressure on coastal and marine ecosystems is high and still increasing in most of the world (Halpern et al., 2008, 2019). Coastal wetlands face direct pressures from urbanisation, land reclamation, pollution and aquaculture (Newton et al., 2020), anthropogenic and climatic stressors on estuaries can be mapped with spatial models (Al-Nasrawi et al., 2018), and nutrient loads from sewage and agriculture have made cultural eutrophication a global problem (Malone & Newton, 2020). Managing these pressures requires knowing where they are, how strong they are and whether water quality responds.

The Amazon estuary is one of the largest estuarine systems in the world. Its eastern sector, the Marajó Bay and the Pará River estuary, receives water from the Tocantins and from the Amazon through the Breves channels. It is a macrotidal system bordered by mangroves, floodplain forests and tidal flats (Souza Filho, 2005), and tides there vary strongly with season and river discharge (Fassoni-Andrade et al., 2023). The estuary holds the Belém metropolitan area and the Vila do Conde port and industrial complex in Barcarena, where alumina and kaolin industries operate. It also holds a large riverine population that depends on the river for water, food and transport (Castello & Macedo, 2016; Zumak et al., 2025).

Evidence of environmental degradation in the area is growing. Studies near the Barcarena industrial area have reported toxicological risk from aluminium, barium, iron and lead in drinking water (de Oliveira et al., 2020). They have also reported changes in benthic macroinvertebrate communities used as bioindicators (Almeida Pinto et al., 2021) and interannual variation in cyanobacteria density (Gomes et al., 2021). Microplastics have been found in fish from the Amazon River estuary (Pegado et al., 2018). Land use in the watersheds around Barcarena has changed rapidly (Furtado et al., 2020). At the same time, access to basic sanitation remains low across municipalities of the Brazilian North (Borges et al., 2025; de Oliveira et al., 2027).

Monitoring has not kept pace. Water-quality stations are few, they are unevenly distributed, and most studies cover one municipality or one stretch of river. Designing a monitoring network is an optimisation problem with many possible criteria, including representativeness, cost and information gain (Jiang et al., 2020). Decision analysis and multivariate statistics have been used to design, assess and rationalise river monitoring networks, including in Brazilian basins (Keum & Kaluarachchi, 2015; Villas-Boas et al., 2017; Calazans et al., 2018; de Souza Fraga et al., 2019). Methods to place stations optimally in estuaries exist (Kim & Hwang, 2020; Alvarez-Vázquez et al., 2023), but they require hydrodynamic models and prior water-quality data, which are scarce in the Amazon. Where such data are lacking, a simpler question can be answered first: where is anthropogenic pressure highest, and are those places being monitored?

Composite indicators are a natural tool for this question. They condense many variables into one comparable score, and they fit the pressure component of the Driver–Pressure–State–Impact–Response (DPSIR) framework widely used in coastal management (Gari et al., 2015). Their results, however, depend on choices of normalisation, weighting and aggregation that are partly arbitrary (OECD & JRC, 2008; Greco et al., 2019). Nominal weights may not reflect the actual influence of each variable (Becker et al., 2017), and objective weighting methods can behave in unexpected ways. The entropy method, for example, can produce abnormal weights in water-quality evaluation (Zhe et al., 2021; Xi et al., 2022). A pressure index meant to guide sampling must therefore show that its ranking survives these choices (Saisana et al., 2005).

Pressure alone is also not enough. The same discharge matters more where people drink untreated river water and have little access to health care. Social vulnerability modifies the consequences of environmental hazards (Cutter et al., 2003; Englund et al., 2023), and equity has become a central

concern in ocean and coastal governance (Bennett et al., 2021). Crossing pressure with vulnerability identifies the places where monitoring matters most for people.

This paper proposes and tests a screening and allocation protocol for water-quality monitoring in data-poor estuaries. The protocol has three steps, which are also the objectives of the paper: (1) to build a municipal Anthropogenic Pressure Index for the Marajó Bay estuary from public data only; (2) to test the robustness of its ranking across weighting schemes, aggregation methods, random weights, data treatments and indicator sets; and (3) to compare pressure and social vulnerability with the current distribution of water-quality stations, to identify monitoring gaps and to estimate what is gained by filling them. The index is part of a larger project that will collect water samples across the estuary, and it was designed to inform the allocation of sampling points. The index is a screening tool for risk-based decisions on monitoring. It does not model or predict water quality. Beyond the method, the paper contributes to public policy. It shows managers where monitoring is missing in relation to pressure and to people, and it turns that diagnosis into a priority list. This matters in regions of high vulnerability and scarce data, such as the Amazon and many coastal areas of emerging countries, where agencies must choose a few sampling points for a very large territory and where populations that use river water directly have the least capacity to detect or avoid contamination.

1.1 Conceptual framework

The index follows the logic of the DPSIR framework (Gari et al., 2015). Drivers are the social and economic forces behind human activity, such as population growth, industrial production and agricultural expansion. Pressures are the direct ways in which those activities act on the environment: discharges of sewage and effluents, shipping, land conversion and emissions. State is the measured condition of the water. Impacts are the consequences for ecosystems and people, and responses are the actions taken by society.

Municipal statistics rarely measure pressures directly. There are no municipal inventories of effluent loads or pollutant discharges in the Amazon. What exists are indicators of drivers and of the capacity to contain pressure: how many people live in a municipality, how many of them lack sewage collection, how much industry and port activity there is, and how fast land is being converted. The index therefore measures potential pressure. It assumes that, other things being

equal, more people without sewage treatment, more industrial and port activity and more land conversion produce a larger load on the adjacent waters. This is the same assumption behind global maps of cumulative human impact, which combine the intensity of drivers with the vulnerability of ecosystems (Halpern et al., 2008, 2019).

Three design principles guided the construction. The first was to use only public and regularly updated data, so that the index can be reproduced and updated by others. The second was to keep pressure and social vulnerability as separate indices. Mixing them in a single score would hide the cases that matter most, where the two coincide. The third was to treat the weights as uncertain from the start and to report the stability of each result, as recommended for composite indicators (OECD & JRC, 2008; Saisana et al., 2005).

2 Materials and methods

2.1 Study area and unit of analysis

The project area is a pentagon drawn over the Marajó Bay estuary. A regular grid of 2,001 candidate sampling points, about 2.2 km apart, was laid over it, and each point was assigned to the municipality whose polygon contains it. Municipalities with at least one grid point entered the analysis (n = 31). Those with 20 or more points are called core municipalities (18), and the others surrounding municipalities (13). Of the 2,001 points, 363 fall in open water outside any municipal polygon. The 31 municipalities had 3,561,294 inhabitants in 2025 (Fig. 1).

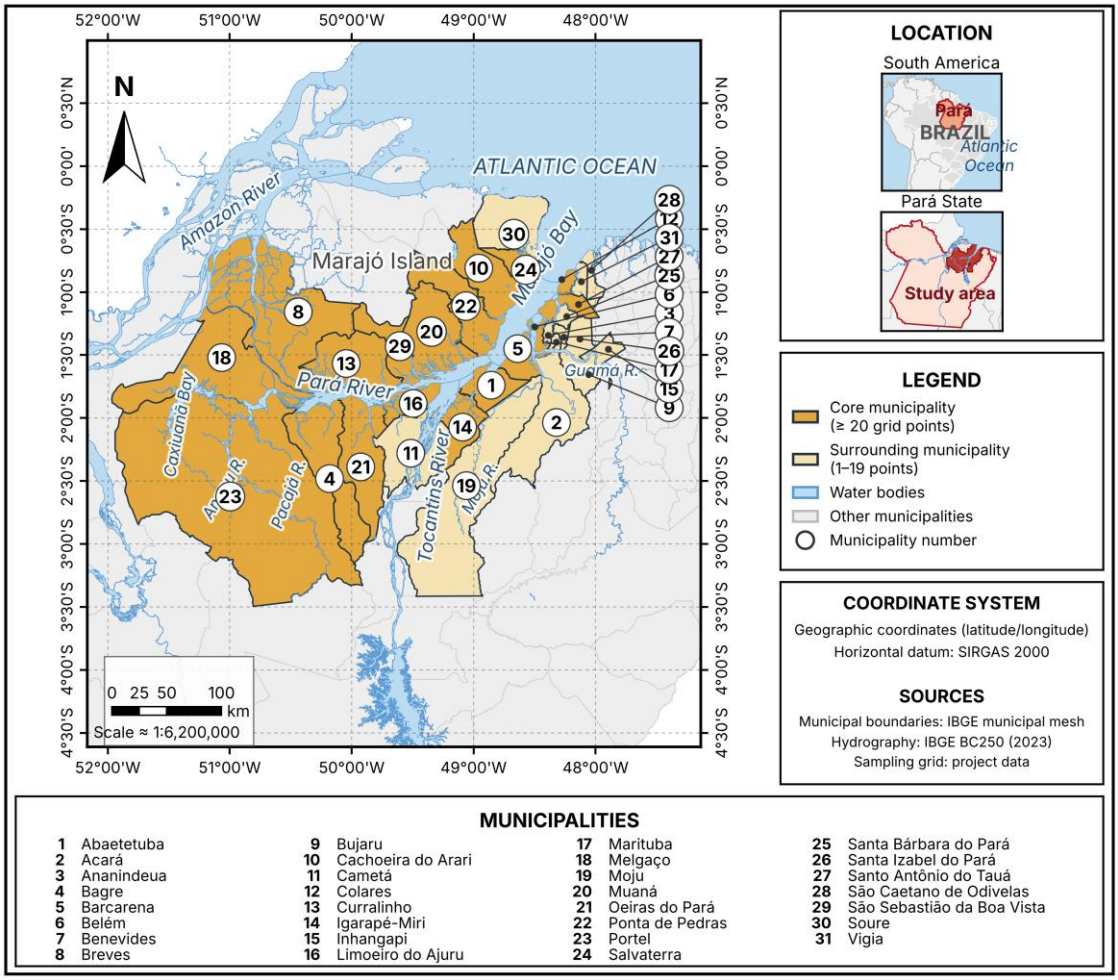


Fig. 1 Study area: the 31 municipalities that share the Marajó Bay estuary, Pará, Brazil. Core municipalities have 20 or more candidate sampling points; surrounding municipalities have 1 to 19. Numbers follow the key in the lower panel; clustered municipalities are labelled with leader lines. Water bodies are shown in blue (IBGE, 1:250,000 continuous cartographic base), with the main rivers and bays named. Side panel: location of Pará in South America and of the study area in Pará, legend, coordinate system and sources. Lower panel: municipality key

2.2 Indicators and data sources

Eighteen municipal indicators were assembled from public secondary sources (Table 1). They were grouped into four pressure dimensions and one social vulnerability dimension:

- **A, demographic and urban:** population and population density.
- **B, sanitation deficit:** share of households without adequate sewage, piped water or waste collection, and the estimated number of people without adequate sewage.

- **C, economic, industrial and port:** industrial value added, exports, port cargo handled and formal jobs in industry.
- **D, land use and environment:** deforestation increment, fire hotspots, greenhouse gas emissions per inhabitant, cattle herd and value of crop production.
- **E, social vulnerability:** vulnerability of families in the federal social registry, under-five mortality and hospitalisations for conditions sensitive to primary care.

The data came from IPS Brasil (2026), which compiles Census 2022 and other official sources, and from the Brazilian Institute of Geography and Statistics (IBGE; municipal GDP, crop and livestock surveys; Instituto Brasileiro de Geografia e Estatística, n.d.-a), the PRODES deforestation monitoring of the National Institute for Space Research (INPE; Instituto Nacional de Pesquisas Espaciais, n.d.), Comex Stat foreign trade statistics (Ministério do Desenvolvimento, Indústria, Comércio e Serviços, n.d.), the RAIS/CAGED formal employment records (Ministério do Trabalho e Emprego, n.d.) and the port statistics of Companhia Docas do Pará (CDP) for 2024 (Companhia Docas do Pará, n.d.). The database was assembled by script, with no manual data entry. In all indicators, higher values mean more pressure or more vulnerability.

Table 1 Indicators, dimensions, transformation and source

Indicator	Dim.	Transf.	Source
Population, 2025	A	log	IPS Brasil 2026 (IBGE)
Population density (inhab./km²)	A	log	IPS Brasil 2026
Households without adequate sewage (%)	B	linear	IPS Brasil 2026 (Census 2022)
Households without piped water (%)	B	linear	IPS Brasil 2026 (Census 2022)
Households without adequate waste collection (%)	B	linear	IPS Brasil 2026 (Census 2022)
People without adequate sewage (estimate)	B	log	Population × sewage deficit
Industrial gross value added (R$ thousand)	C	log	IBGE, municipal GDP
Exports (US$)	C	log	Comex Stat
Port cargo handled, 2024 (t)	C	log	Companhia Docas do Pará
Formal jobs in industry	C	log	RAIS/CAGED
Deforestation increment (km²)	D	log	PRODES/INPE
Fire hotspots (IPS scale)	D	linear	IPS Brasil 2026 (INPE)
CO_2e emissions per inhabitant	D	log	IPS Brasil 2026 (SEEG)

Indicator	Dim.	Transf.	Source
Cattle herd (head)	D	log	IBGE, PPM
Value of crop production (R$ thousand)	D	log	IBGE, PAM
Vulnerability of families in the social registry (IVCAD)	E	linear	IPS Brasil 2026 (MDS)
Under-five mortality	E	linear	IPS Brasil 2026 (DATASUS)
Hospitalisations for primary-care-sensitive conditions	E	linear	IPS Brasil 2026 (DATASUS)

Port cargo was assigned to the municipality where each public port is located (Belém, including the Outeiro and Miramar terminals, and Vila do Conde, in Barcarena). The ports of the area handled 24.6 million tonnes in 2024. The number of people without adequate sewage was estimated as the product of population and the share of households without adequate sewage. It adds a measure of absolute load to the percentage deficits: a small municipality with a very high deficit and a large city with a moderate deficit can discharge similar volumes of untreated sewage. In the study area, about 1.54 million people (43% of the population) live in households without adequate sewage. A climate vulnerability index available in the same source was tested in dimension E and removed. It describes the exposure of the territory to climate hazards rather than the susceptibility of the population, and its negative relation with the other three indicators (Cronbach's α became negative) confirmed that it does not belong to the same construct.

The monitoring network was described with the inventory of water-quality stations in operation in the HidroWeb system of the National Water and Sanitation Agency (ANA), consulted in October 2026 (Agência Nacional de Águas e Saneamento Básico, n.d.). No measurement of water quality enters the index or the analysis.

2.3 Transformation, winsorisation and normalisation

Magnitude indicators (population, density, people without adequate sewage, value added, exports, cargo, jobs, deforestation, emissions, cattle and crops) are strongly right-skewed: Belém and Barcarena are orders of magnitude above the other municipalities. These indicators were transformed with the shifted natural logarithm, which accepts zeros:

$$x'_{ij} = \ln\left(1 + x_{ij}\right) \tag{1}$$

Household percentages and index-scale indicators were kept on a linear scale (Table 1). Population density and emissions per inhabitant, although ratios, were log-transformed because

they are as skewed as the totals. To limit the influence of remaining extreme values, each indicator was then winsorised at the 2.5th and 97.5th percentiles (Dixon, 1960):

$$x''_{ij} = \min\left(\max\left(x'_{ij},\, Q_j(0.025)\right),\, Q_j(0.975)\right) \tag{2}$$

and min–max normalised to the interval [0, 1]:

$$z_{ij} = \frac{x''_{ij} - \min_i x''_{ij}}{\max_i x''_{ij} - \min_i x''_{ij}} \tag{3}$$

2.4 Dimension scores and the pressure index

The score of municipality i in dimension k is the arithmetic mean of its normalised indicators, where J_k is the set of indicators in dimension k:

$$S_{ik} = \frac{1}{|J_k|}\sum_{j \in J_k} z_{ij}\,, \qquad k \in \{A, B, C, D, E\} \tag{4}$$

The Anthropogenic Pressure Index for the Estuary (APEI) is the weighted sum of the four pressure dimensions (simple additive weighting, SAW):

$$\mathrm{APEI}_i = \sum_{k \in \{A,B,C,D\}} w_k\, S_{ik}, \qquad \sum_k w_k = 1 \tag{5}$$

The Social Vulnerability Index (SVI) is the score of dimension E, $\mathrm{SVI}_i = S_{iE}$. It was kept separate from the APEI so that pressure and vulnerability could be crossed.

Indicators were averaged within each dimension, and the dimensions received equal weights. Together, these choices give each dimension the same importance in the APEI regardless of how many indicators it contains, and it prevents the land-use dimension, with five indicators, from dominating the demographic dimension, with two.

2.5 Rationale and assumptions of the construction

The APEI uses standard operations of composite indicators. Their combination for estuarine pressure is new, so the main choices are justified here. The full account of reasons, assumptions and weaknesses is given in Online Resource 1. Substituting Eq. 4 into Eq. 5 gives the index as a single weighted sum of the 15 normalised pressure indicators:

$$\mathrm{APEI}_i = \sum_k \sum_{j \in J_k} \frac{w_k}{|J_k|} z_{ij} \tag{6}$$

The effective weight of an indicator is $w_k/|J_k|$. With equal dimension weights it is 0.125 for each demographic indicator, 0.0625 for each sanitation and economic indicator and 0.05 for each land-use indicator. The scale is relative to the 31 municipalities. The index orders them and is not an absolute measure of load.

Four choices carry assumptions that matter for reading the results. The logarithm assumes that equal proportional increases in a source count equally. Without it the index would only separate Belém and Barcarena from the rest. The dimensions are added, not multiplied, because pressures from different sources accumulate in the same receiving waters, and a municipality with no industry and a large sanitation deficit still exerts pressure. Addition implies full compensation between dimensions, makes the weights trade-off rates and not measures of importance (Munda & Nardo, 2009), and ignores interactions between stressors (Crain et al., 2008). Equal weights are the baseline because there are no measured loads with which to calibrate them. Finally, the index mixes municipal totals with five rates and counts population twice, directly and through the number of people without sewage. Each choice is matched by a test reported in the Results.

2.6 Weighting schemes

Five weighting schemes were compared (Table 2). The baseline uses equal weights. Two thematic schemes represent the views of different users: a water quality focus, which raises the weight of the sanitation deficit, and a land use focus, which raises the weight of land use and environment. Two objective schemes derive weights from the data. Shannon entropy gives more weight to dimensions whose scores are more unevenly distributed (Lotfi & Fallahnejad, 2010):

$$E_k = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ik} \ln p_{ik}, \qquad p_{ik} = \frac{S_{ik}}{\sum_i S_{ik}}, \qquad w_k = \frac{1 - E_k}{\sum_l (1 - E_l)} \tag{7}$$

CRITIC combines the dispersion of each dimension with its conflict with the others, measured by the Pearson correlation r_{kl} (Diakoulaki et al., 1995):

$$C_k = \sigma_k \sum_l (1 - r_{kl}), \qquad w_k = \frac{C_k}{\sum_l C_l} \tag{8}$$

Table 2 Weights of the four pressure dimensions under five weighting schemes

Dimension	Equal	Water quality focus	Land use focus	Entropy	CRITIC
A Demographic and urban	0.250	0.200	0.200	0.229	0.233
B Sanitation deficit	0.250	0.400	0.200	0.141	0.283
C Economic, industrial and port	0.250	0.250	0.200	0.494	0.249
D Land use and environment	0.250	0.150	0.400	0.136	0.234

2.7 Alternative aggregation methods

To check the influence of the aggregation rule, the ranking was recomputed with two other multicriteria methods. TOPSIS ranks alternatives by their relative closeness to an ideal solution (Hwang & Yoon, 1981). With vector-normalised and weighted scores v_{ik}, ideal values v_k^+ and v_k^-, and Euclidean distances D_i^+ and D_i^- to them, the closeness coefficient is:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{9}$$

PROMETHEE II ranks alternatives by net outranking flow (Brans & Vincke, 1985). For each pair of municipalities (a, b) and each dimension, the preference degree $P_k(a, b)$ was computed with a linear preference function, with an indifference threshold of zero and a strict preference threshold equal to the standard deviation of the dimension. The net flow is:

$$\phi(a) = \frac{1}{n-1} \sum_{b \neq a} \sum_k w_k \left[P_k(a, b) - P_k(b, a) \right] \tag{10}$$

Here “preferred” means “exerts more pressure”.

2.8 Robustness, consistency and profiles

Agreement between rankings was measured with Spearman’s rank correlation ρ. Uncertainty in the weights was explored by Monte Carlo simulation with 5,000 weight vectors drawn uniformly from the simplex, that is, from a Dirichlet(1, 1, 1, 1) distribution (Butler et al., 1997). For each municipality we recorded the probability of ranking among the five highest-pressure municipalities, the median rank and the 95% rank interval. These quantities correspond to the rank acceptability indices of stochastic multicriteria acceptability analysis (Lahdelma et al., 1998).

The weights are only one of the choices behind a composite indicator (Saisana et al., 2005). Five further tests were therefore applied to the equal-weight APEI. (i) Each of the 15 pressure

indicators, and then each of the four dimensions, was removed in turn. (ii) The data treatment was varied: no winsorisation, winsorisation at the 5th and 95th percentiles, rank-based and z-score normalisation in place of min–max, no logarithmic transformation, a geometric mean of the dimensions in place of the arithmetic mean (computed on the dimension scores shifted by 0.01, so that zero scores remain defined; z-scores were rescaled to [0, 1] before aggregation), and a flat mean of the 15 indicators without dimensions. (iii) An intensity variant was computed, in which eight magnitude indicators (people without adequate sewage, industrial value added, exports, port cargo, industrial jobs, deforestation, cattle and crops) were divided by municipal area and population was dropped, to separate total load from load per unit area. (iv) The Monte Carlo simulation was repeated at the indicator level, with weights drawn from a Dirichlet distribution over the 15 indicators. (v) A joint uncertainty analysis combined all sources in 10,000 runs. In each run the dimension weights were drawn from the simplex, and the winsorisation rule (2.5–97.5, 5–95 or none), the normalisation (min–max, rank or z-score), the aggregation function (arithmetic or geometric mean) and the exclusion of one random indicator (with probability 0.5) were drawn at random. For each municipality we recorded the probability of ranking among the five highest and the probability of having above-median pressure. (vi) Three data choices were tested separately. The public sources record an absent activity and an unreported one in the same way, so a missing record cannot be told apart from a true zero (Online Resource 1, Table S4). The zeros of exports, industrial jobs, deforestation and cattle were therefore replaced, first by half of the smallest positive value and then by the median of the positive values, which is an upper bound. Port cargo from private terminals, which the CDP data omit, was represented by multiplying the cargo of Barcarena, where the private terminals of the Vila do Conde complex operate, by two and by three. (vii) Because the municipality is not a hydrological unit, a connectivity variant multiplied the APEI by $e^{-d_i/L}$, where d_i is the distance from municipality i to the nearest large water body of the estuary (water polygons larger than 200 km² in the IBGE 1:250,000 base: Marajó Bay, the Pará River, the Breves channels and the lower Tocantins) and L is 25 or 50 km. Finally, 95% bootstrap intervals for the Spearman correlation between each weighting scheme and the baseline were obtained from 2,000 resamples of the municipalities. They show how much the agreement depends on the particular set of municipalities. The 31 municipalities are the complete set of interest and not a sample, so no tests of statistical

significance are reported, with the exception of the permutation reference for Moran's I described below.

Spatial clustering was described with global Moran's I and a first-order contiguity matrix (Moran, 1950). Two municipalities were neighbours when their boundaries share at least one point (queen contiguity), the weights were binary and not row-standardised, and the matrix has 71 links, with two to eight neighbours per municipality (median five). Every municipality, including those on Marajó Island, has at least one neighbour. The list of neighbours is given in Online Resource 1 (Table S6). The observed value was compared with the values obtained in 9,999 random reassignments of the scores among municipalities. Correlations between dimensions are Pearson coefficients; correlations between rankings, and between the number of stations and the APEI, are Spearman coefficients.

The indicators of each dimension are formative: they are distinct sources of pressure, not interchangeable measures of one latent trait. Cronbach's α (Cronbach, 1951) is therefore reported only as a description of the redundancy among the indicators of each dimension, not as a test of the measurement model. Municipalities were grouped by their four pressure scores with the k-means algorithm (Lloyd, 1982), with k-means++ initialisation and 50 restarts. The mean silhouette width (Rousseeuw, 1987) and the gap statistic (Tibshirani et al., 2001; 100 uniform reference data sets, smallest K whose gap is within one standard error of the next) were computed for K = 2 to 6 (K = 1 to 6 for the gap statistic), and the stability of the K = 3 solution was assessed by clustering 200 resamples of the municipalities and comparing each partition with the original one through the adjusted Rand index (Hubert & Arabie, 1985).

2.9 Risk screening, monitoring gaps and allocation exercise

The analysis is a risk screening. Risk is read as the coincidence of three conditions: high potential pressure, which is the hazard; high social vulnerability, which is the susceptibility of the exposed population; and the absence of monitoring, which is the lack of capacity to detect a problem. A screening of this kind is not judged by how well it predicts a measurement. It is judged by its transparency, by the robustness of its ordering and by its usefulness for the decision it supports.

Pressure and vulnerability were crossed in a 2 × 2 matrix with cut-offs at the medians of the APEI (equal weights) and the SVI. Each municipality was then compared with the number of

ANA water-quality stations in operation. A monitoring gap was defined as a municipality with pressure at or above the median and no station. The municipality at the median of the APEI (Bujaru) is placed in the high-pressure group. Because a median cut-off is a convention, the matrix was repeated with cut-offs at the upper terciles, and each gap was qualified by the probability of above-median pressure in the joint uncertainty analysis. A gap was considered robust when this probability was at least 80%, a conventional threshold that a manager can move because the probabilities are reported. To show how the first tier depends on it, the threshold was varied from 60% to 95% in steps of 5 points. To express the gain from acting on the result, a simple allocation exercise was carried out. One new station was assigned to each of four or eight unmonitored municipalities under three rules: the priority rule of this paper, pressure only (highest APEI) and population only (largest population). The priority rule takes first the unmonitored municipalities with vulnerability at or above the median and a robust pressure gap (Tier 1 in Table 5), then the unmonitored municipalities with high pressure and lower vulnerability (Tier 3), each tier in decreasing order of APEI. Municipalities whose high pressure is not robust (Tier 2) are referred to field confirmation and do not receive a station in the exercise. Coverage was measured by the share of the population, and of the people without adequate sewage, who live in a municipality with at least one station, in the whole area and in the 16 municipalities with vulnerability at or above the median. Because the number of people without adequate sewage is also an indicator of the APEI, the share of the territory (area) of the municipalities with a station was added as a metric that does not depend on the index. The rules were also compared with explicit optima: the four unmonitored municipalities that maximise each metric. Because every metric is a sum over municipalities, the optimum with four new stations is obtained exactly by taking the four unmonitored municipalities with the largest values. One station in a municipality is a minimum condition for detection. It is not adequate coverage, least of all in the largest municipalities.

An exploratory comparison with measured water quality used the open database of the state programme QUALIÁGUA (Secretaria de Estado de Meio Ambiente e Sustentabilidade do Pará, n.d.), which holds 1,797 samples from 181 stations between 2016 and 2024. For each station we computed the median of each parameter and the share of samples that exceeded at least one class 2 limit of CONAMA Resolution 357 (Conselho Nacional do Meio Ambiente, 2005): dissolved oxygen below 5 mg/L, thermotolerant coliforms above 1,000 per 100 mL, BOD above 5 mg/L,

total phosphorus above 0.1 mg/L, turbidity above 100 NTU or pH outside 6–9. The freshwater limits were applied to all stations as a common reference, although some stations in the bay are brackish. Station and municipal summaries were compared with the APEI and the dimension scores through Spearman correlations. This is a plausibility check and not a validation, because the stations were not placed to represent municipal loads.

All calculations were done in Python, with a fixed random seed. Maps use the municipal boundaries and the 1:250,000 water bodies of IBGE (Instituto Brasileiro de Geografia e Estatística, n.d.-b). The code and data are openly available (see Data availability).

Use of artificial intelligence tools. The study design, the index, the methodological choices and the interpretation of the results were defined and validated by the authors. A large language model, Claude (Anthropic), was used as an assistive tool, always from the authors' specifications, to code the calculations and figures in Python, to typeset the equations, to draft and edit the English text, and to check the metadata of every reference against Crossref or the publisher's record. The authors verified all outputs and take full responsibility for the content.

3 Results

3.1 Pressure ranking

With equal weights, the APEI ranged from 0.137 in Soure to 0.671 in Barcarena (Table 3, Fig. 2). The five highest scores were Barcarena (0.671), Belém (0.606), Moju (0.605), Acará (0.558) and Abaetetuba (0.543). The lowest were Salvaterra (0.271), Colares (0.204) and Soure (0.137).

The highest pressure is concentrated on the eastern and southern margins of the estuary, from the Belém metropolitan area through Barcarena and Abaetetuba to the Moju and Acará river basins (Fig. 2). Marajó Island and the north-eastern coast have the lowest scores. Portel, in the far west, is an exception: it ranks seventh because of its very high land-use pressure.

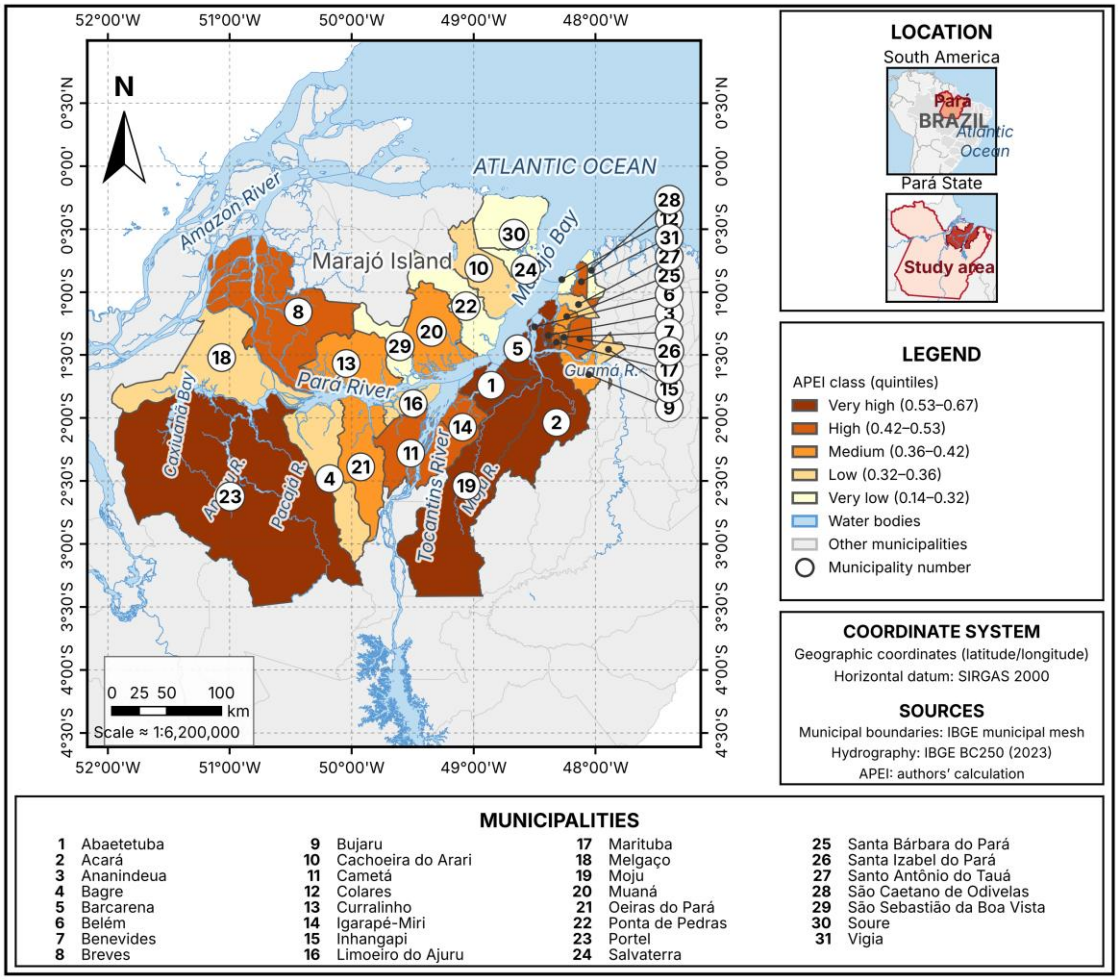


Fig. 2 Anthropogenic Pressure Index for the Estuary (APEI, equal weights) by quintile class

Table 3 APEI under five weighting schemes, TOPSIS closeness and PROMETHEE II net flow with equal weights, and Monte Carlo results (5,000 draws): probability of ranking among the five highest (P5), median rank (Med.) and 95% rank interval. PROM.: PROMETHEE II net flow. Municipalities are ordered by the equal-weight APEI. An asterisk marks core municipalities

#	Municipality	Equal	Water	Land	Entropy	CRITIC	TOPSIS	PROM.	P5 %	Med.	95% int.
1	Barcarena *	0.671	0.711	0.616	0.776	0.678	0.658	0.504	88.2	2	1–10
2	Belém *	0.606	0.589	0.514	0.774	0.597	0.623	0.129	60.3	3	1–27
3	Moju	0.605	0.590	0.669	0.555	0.605	0.553	0.433	65.5	3	1–12
4	Acará	0.558	0.581	0.608	0.455	0.567	0.484	0.406	53.0	5	1–13
5	Abaetetuba *	0.543	0.559	0.527	0.531	0.545	0.524	0.371	36.5	6	4–13
6	Ananindeua	0.540	0.542	0.453	0.631	0.535	0.564	0.109	48.2	7	2–29
7	Portel *	0.526	0.546	0.582	0.431	0.534	0.459	0.306	37.5	8	3–16
8	Santa Izabel do Pará	0.521	0.510	0.535	0.512	0.519	0.507	0.341	20.5	7	4–18
9	Igarapé-Miri *	0.516	0.566	0.509	0.469	0.527	0.460	0.351	24.3	8	3–12
10	Cametá	0.490	0.519	0.501	0.383	0.497	0.425	0.293	12.1	9	4–17
11	Marituba	0.477	0.491	0.413	0.525	0.476	0.493	0.073	24.0	11	3–27

#	Municipality	Equal	Water	Land	Entropy	CRITIC	TOPSIS	PROM.	P5 %	Med.	95% int.
12	Breves *	0.464	0.550	0.423	0.422	0.483	0.410	0.162	13.7	12	2–24
13	Vigia	0.417	0.422	0.415	0.390	0.418	0.381	0.074	0.0	15	9–22
14	Benevides	0.399	0.340	0.392	0.486	0.384	0.454	0.058	5.8	14	5–30
15	Oeiras do Pará *	0.398	0.427	0.446	0.266	0.407	0.345	0.015	5.1	17	4–22
16	Bujaru	0.398	0.416	0.439	0.299	0.404	0.344	0.008	0.4	17	7–20
17	Santa Bárbara do Pará	0.386	0.391	0.385	0.407	0.388	0.369	-0.042	0.0	17	10–24
18	Muaná *	0.365	0.425	0.361	0.276	0.379	0.308	-0.102	0.0	18	12–24
19	Curralinho *	0.356	0.449	0.345	0.227	0.377	0.314	-0.147	4.4	20	4–27
20	Bagre *	0.351	0.391	0.387	0.215	0.362	0.307	-0.099	0.0	20	10–27
21	Santo Antônio do Tauá *	0.346	0.294	0.381	0.374	0.336	0.357	-0.039	0.0	18	10–29
22	Inhangapi	0.345	0.326	0.389	0.340	0.344	0.335	-0.114	0.0	20	9–29
23	Melgaço *	0.335	0.418	0.341	0.207	0.356	0.301	-0.188	0.6	23	8–30
24	Limoeiro do Ajuru *	0.318	0.402	0.295	0.212	0.337	0.283	-0.240	0.0	23	10–29
25	Cachoeira do Arari *	0.316	0.356	0.342	0.213	0.327	0.273	-0.228	0.0	23	15–27
26	São Caetano de Odivelas	0.302	0.304	0.341	0.214	0.304	0.258	-0.249	0.0	24	14–28
27	São Sebastião da Boa Vista *	0.286	0.365	0.267	0.187	0.304	0.258	-0.322	0.0	26	15–31
28	Ponta de Pedras *	0.272	0.298	0.301	0.177	0.280	0.234	-0.357	0.0	27	19–29
29	Salvaterra *	0.271	0.249	0.294	0.266	0.267	0.242	-0.301	0.0	27	18–30
30	Colares *	0.204	0.230	0.210	0.132	0.210	0.160	-0.549	0.0	30	26–31
31	Soure	0.137	0.122	0.155	0.118	0.135	0.085	-0.658	0.0	31	28–31

Figure 3 shows what drives each score. Barcarena combines the highest economic, industrial and port score (0.99) with a high sanitation deficit (0.72). Belém has the highest demographic score (0.98) and a high economic score (0.98), but relatively low sanitation deficit and land-use pressure. Moju and Acará reach the top five by a different route: very high land-use pressure (0.93 and 0.81) and a high sanitation deficit, with moderate urban and industrial scores.

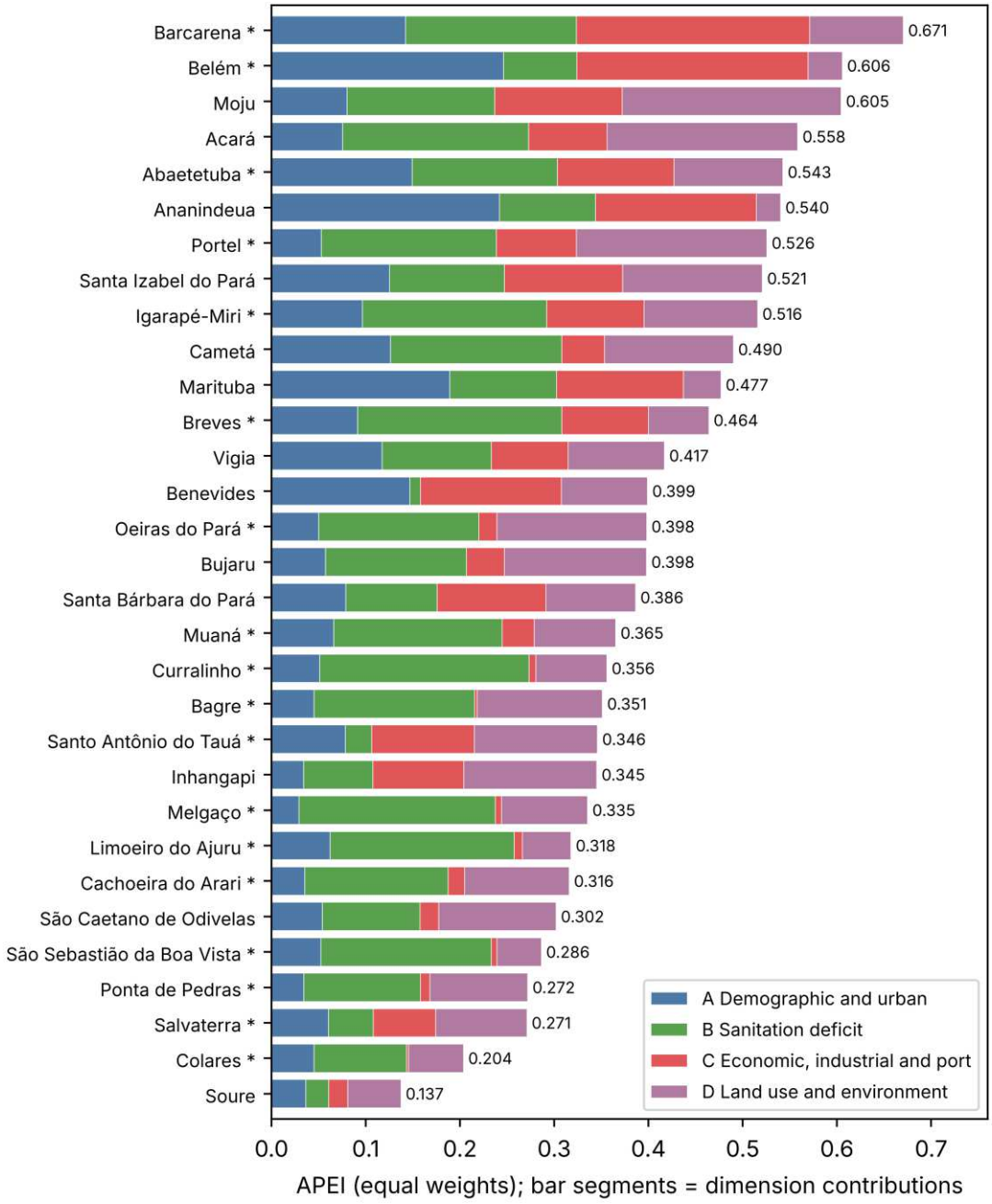


Fig. 3 Ranking of the APEI with the contribution of each pressure dimension (equal weights). An asterisk marks core municipalities

3.2 Pressure profiles

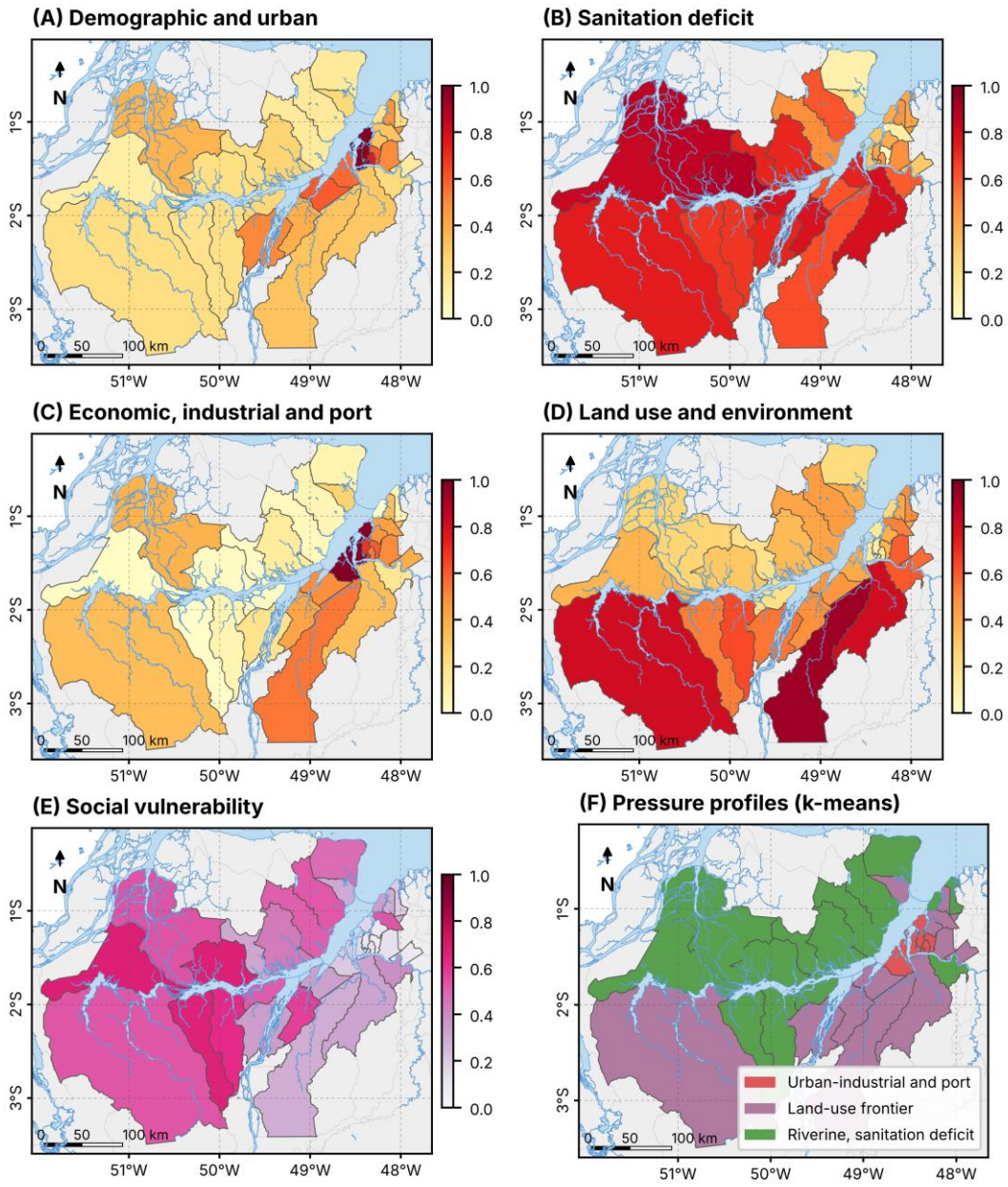
The four pressure dimensions have distinct spatial patterns (Fig. 4; Online Resource 1, Table S1). Demographic and economic pressure concentrate around Belém and Barcarena. The sanitation

deficit is high almost everywhere outside the metropolitan area and highest on Marajó Island (Curralinho 0.89, Breves 0.87, Melgaço 0.83). Land-use pressure is highest in the south, in Moju, Acará and Portel.

The k-means analysis grouped the municipalities into three profiles (Fig. 4, bottom right). The separation is weak. The mean silhouette width was 0.274 for K = 3, against 0.394 for K = 2 and 0.315 to 0.333 for K = 4 to 6, and the median adjusted Rand index between the original partition and partitions of resampled data was 0.51. The gap statistic also selected K = 2 (Online Resource 1, Table S5). Two groups, metropolitan and non-metropolitan, are therefore the clearest statistical split. Three groups were kept because the division of the non-metropolitan municipalities into a land-use frontier and a riverine group has a direct use in the choice of monitoring parameters. The profiles should be read as predominant types with fuzzy borders, not as classes.

- **Urban-industrial and port** (5 municipalities): Barcarena, Belém, Ananindeua, Marituba and Benevides. Centroid (A, B, C, D) = (0.77, 0.39, 0.76, 0.23).
- **Land-use frontier** (12): Moju, Acará, Abaetetuba, Portel, Santa Izabel do Pará, Igarapé-Miri, Cametá, Vigia, Santa Bárbara do Pará, Santo Antônio do Tauá, Inhangapi and Salvaterra. Centroid = (0.36, 0.52, 0.39, 0.57).
- **Riverine with a sanitation deficit** (14): mostly municipalities of Marajó Island, including Breves, Curralinho, Melgaço, Bagre and Muaná. Centroid = (0.20, 0.63, 0.08, 0.38).

Salvaterra illustrates the fuzzy borders. It is on Marajó Island but joins the land-use frontier because its sanitation deficit (0.19) is far below that of the riverine group (centroid 0.63); its distances to the two centroids are similar (0.42 and 0.48). Each profile calls for different monitoring parameters. In the first, industrial effluents, metals and port activity dominate. In the second, sediments, nutrients and agrochemicals from land conversion are the main concern. In the third, the main pressure is untreated domestic sewage, and the relevant parameters are microbiological and organic.



Scores normalised 0–1 (1 = highest pressure or vulnerability). Datum SIRGAS 2000; geographic coordinates. Sources: IBGE; authors' calculation.

Fig. 4 Scores of the four pressure dimensions (A–D), social vulnerability (E) and pressure profiles from k-means clustering

3.3 Robustness of the ranking

The ranking changed little across weighting schemes and aggregation methods (Online Resource 1, Table S2). Spearman correlations with the equal-weight ranking were 0.994 for CRITIC (95% bootstrap interval 0.970–1.000), 0.959 for the land-use focus (0.900–0.977), 0.923 for entropy

(0.827–0.966) and 0.922 for the water-quality focus (0.793–0.970); between pairs of schemes they ranged from 0.764 to 0.994. The largest shift came from entropy, which assigned 49.4% of the weight to the economic, industrial and port dimension, because this dimension is the most unevenly distributed. Correlations between SAW and the other methods were 0.973 for TOPSIS and 0.966 for PROMETHEE II.

Barcarena ranked first under four of the five weighting schemes and under both alternative methods (Table 3). Under the land-use focus it was second, after Moju. In the Monte Carlo simulation, it was among the five highest-pressure municipalities in 88.2% of the 5,000 draws, followed by Moju (65.5%), Belém (60.3%) and Acará (53.0%) (Fig. 5). No other municipality exceeded 50%. Ananindeua (48.2%), Portel (37.5%) and Abaetetuba (36.5%) formed a second group.

The rank intervals reveal differences that the scores hide (Table 3). Barcarena, Moju and Acará never fall below rank 13 (intervals 1–10, 1–12 and 1–13). Belém and Ananindeua have very wide ones (1–27 and 2–29). Their pressure is concentrated in the demographic and economic dimensions, so they rank near the top when those dimensions carry weight and fall sharply when sanitation and land use dominate. At the other end, Soure and Colares remain in the bottom of the ranking in every draw (intervals ending at ranks 31 and 26–31).

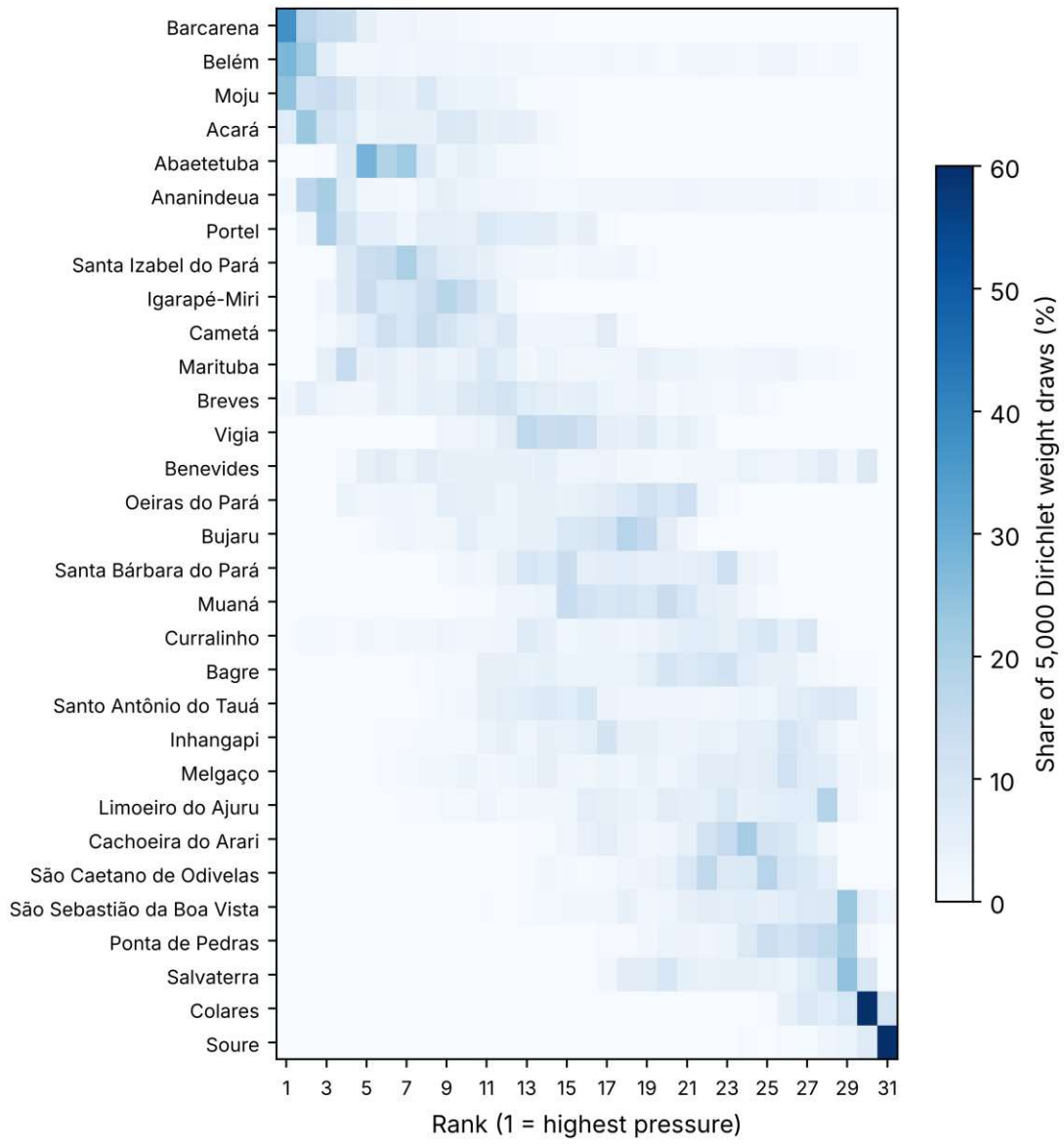


Fig. 5 Distribution of the rank of each municipality over 5,000 random weight vectors (Monte Carlo). Darker cells indicate ranks attained more often

The agreement between the three aggregation methods is worth noting, because they rest on different principles. SAW is fully compensatory: a high score in one dimension offsets a low score in another. TOPSIS measures distance to the best and worst observed profiles. PROMETHEE II is based on pairwise comparisons and limits compensation through its preference thresholds. The three methods agreed on Barcarena as the first municipality and on Colares and Soure as the last two. The main difference concerned Belém and Ananindeua. Their

PROMETHEE II net flows (0.129 and 0.109) place them 10th and 11th, well below their SAW ranks (2nd and 6th), because in pairwise comparisons their low land-use pressure and moderate sanitation deficit count against them in two of the four dimensions.

3.4 Uncertainty beyond the weights

The ranking was little affected by the removal of single indicators. Spearman correlations with the baseline were 0.971 or higher for the 15 leave-one-indicator-out indices, and no municipality moved more than six positions. Removing a whole dimension had a larger effect (ρ from 0.843 without the demographic dimension to 0.927 without land use), and in each case three of the five baseline leaders stayed in the top five. Barcarena stayed in the top five in all four cases and Moju in three.

The data treatment mattered less than the weights, with one exception. Changing the winsorisation limits or using z-scores left the ranking almost unchanged ($\rho \geq 0.995$). Rank-based normalisation (0.968), the flat mean of indicators (0.956) and the geometric mean (0.921) changed it moderately. Removing the logarithmic transformation had the largest effect (0.858), because untransformed magnitudes let Belém dominate every magnitude indicator.

The intensity variant changed the ranking more than any weighting scheme ($\rho = 0.789$), and three of the five leaders changed. With magnitudes expressed per square kilometre, the five highest municipalities were Barcarena, Ananindeua, Marituba, Belém and Santa Izabel do Pará. Small and dense metropolitan municipalities rose, and large municipalities with extensive land conversion, such as Moju, Acará and Portel, fell. Barcarena was first in both versions. The APEI is thus an index of total potential load per municipality. This is the relevant quantity for deciding how many sampling points a municipality deserves, but it is not a measure of pressure per unit of area or of shoreline.

The construction issues identified in the Methods had little effect. Without the number of people without sewage, which counts population a second time, the correlation with the baseline was 0.988. Without population density it was 0.971, and without both 0.944. When every rate was converted to an absolute number, so that the index measured only total load, it was 0.977 and no municipality moved more than four positions. Barcarena and Moju stayed in the top five in all four variants, and Belém led the load-only version. The five unmonitored municipalities with

high pressure and high vulnerability were the same in all of them. The baseline therefore behaves as an index of total load, and its double counting of population is not what produces the results.

When the Monte Carlo simulation was run over the 15 indicators, Moju (95.9%), Barcarena (92.9%) and Acará (80.8%) were the municipalities most often in the top five, followed by Portel (63.4%) and Belém (41.2%). In the joint uncertainty analysis, the median correlation with the baseline ranking was 0.858 (5th percentile 0.504). Barcarena remained in the top five in 86.6% of the 10,000 runs, followed by Moju (62.5%), Abaetetuba (57.4%), Acará (52.3%), Belém (45.8%) and Santa Izabel do Pará (44.5%). Barcarena, Moju and Acará were the only municipalities in the top five in more than half of the runs in all three simulations (weights, indicators and joint analysis), and they form the robust top of the ranking. The position of Belém depends on the treatment of magnitudes and on the weight given to the demographic and economic dimensions.

The other data choices had small effects. Replacing the zeros of the four affected indicators by half of the smallest positive value left the ranking almost unchanged ($\rho = 0.998$). Replacing them by the median of the positive values, an extreme assumption, gave $\rho = 0.956$: Ananindeua replaced Acará in the top five, and Barcarena, Moju and Belém stayed in it. Doubling or tripling the port cargo of Barcarena to represent private terminals did not change the ranking ($\rho = 1.000$), because Barcarena already has the highest cargo and its normalised score is at the upper limit. The connectivity variant lowered the agreement with the baseline ($\rho = 0.810$ with $L = 50$ km and 0.583 with $L = 25$ km), because it penalises inland municipalities such as Inhangapi, Bujaru and Santa Izabel do Pará (26 to 50 km from the main water bodies). The top three (Barcarena, Belém and Moju) did not change, and the four unmonitored municipalities of Tier 1 ranked between 5th and 8th with both values of L, above the median.

Pressure was spatially clustered. Moran's I was 0.406 for the APEI, and fewer than 0.1% of the random reassignments reached that value. Clustering was strongest for the sanitation deficit (0.481) and the economic dimension (0.426) and weakest for land use (0.187). Social vulnerability was also clustered (0.502).

3.5 Internal consistency

Cronbach's α ranged from 0.704 to 0.889 for the four pressure dimensions (Online Resource 1, Table S3), which indicates that the indicators of each dimension overlap substantially. It was

lower for social vulnerability (0.549), which has only three indicators. Among dimensions, the strongest correlation was between the demographic and the economic dimensions (0.804): large cities concentrate industry and ports. The economic dimension was negatively correlated with social vulnerability (−0.625), which means that industrial municipalities are, on average, less socially vulnerable. The APEI itself was only weakly related to the SVI ($\rho = -0.25$). Pressure and vulnerability therefore carry different information.

3.6 Pressure, vulnerability and monitoring gaps

The medians of the APEI (0.398) and the SVI (0.334) divide the municipalities into four groups (Fig. 6):

- **High pressure and high vulnerability** (6): Portel, Igarapé-Miri, Cametá, Breves, Oeiras do Pará and Bujaru.
- **High pressure and low vulnerability** (10): Barcarena, Belém, Moju, Acará, Abaetetuba, Ananindeua, Santa Izabel do Pará, Marituba, Vigia and Benevides.
- **Low pressure and high vulnerability** (10): Muaná, Curralinho, Bagre, Santo Antônio do Tauá, Melgaço, Limoeiro do Ajuru, Cachoeira do Arari, Ponta de Pedras, Colares and Soure.
- **Low pressure and low vulnerability** (5): Santa Bárbara do Pará, Inhangapi, São Caetano de Odivelas, São Sebastião da Boa Vista and Salvaterra.

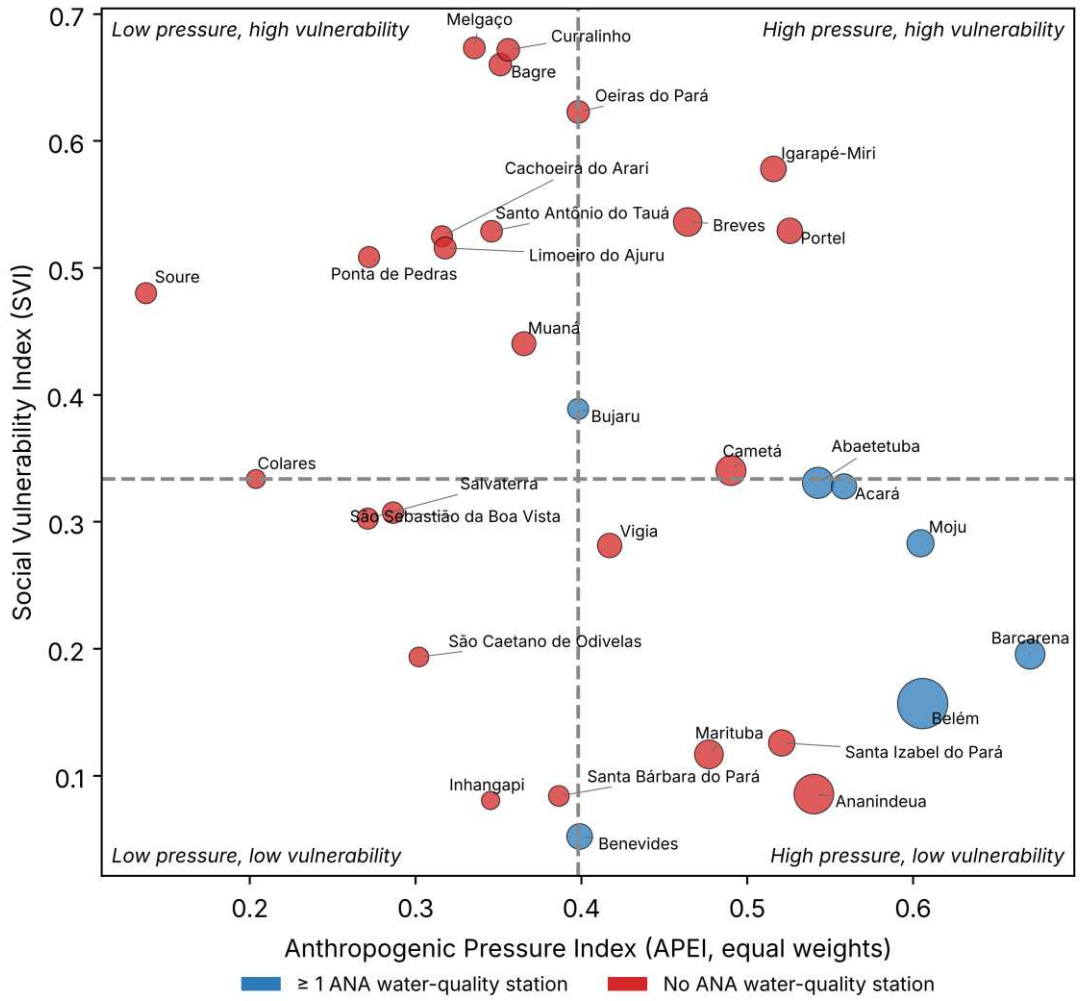


Fig. 6 Risk matrix: anthropogenic pressure (APEI) against social vulnerability (SVI). Dashed lines are the medians, bubble size is proportional to population, and colour shows whether the municipality has at least one ANA water-quality station in operation

The monitoring network follows pressure only in part. The 31 ANA water-quality stations in operation in the area are located in seven municipalities: Barcarena (10), Moju (8), Acará (4), Abaetetuba (3), Belém (3), Bujaru (2) and Benevides (1). The number of stations is positively correlated with the APEI ($\rho = 0.61$), so the network does concentrate where pressure is highest. But 24 municipalities have no station at all, and nine of the 16 municipalities with pressure at or above the median are among them: Ananindeua, Portel, Santa Izabel do Pará, Igarapé-Miri, Cametá, Marituba, Breves, Vigia and Oeiras do Pará (Fig. 7).

The gap is widest where pressure meets vulnerability. Of the six municipalities in the high-pressure and high-vulnerability group, five have no station: Portel, Igarapé-Miri, Cametá, Breves and Oeiras do Pará. Only Bujaru has stations. The 10 municipalities with low pressure and high vulnerability, most of them on Marajó Island, also have no ANA stations.

The joint uncertainty analysis shows which of these gaps are firm. Among the unmonitored municipalities, the probability of above-median pressure was 100% for Igarapé-Miri, 97% for Santa Izabel do Pará, 91% for Cametá, 89% for Portel and 80.3% for Breves. It was lower for Vigia (70%), Ananindeua (67%) and Marituba (65%), and only 42% for Oeiras do Pará, whose baseline score lies just above the median. Four unmonitored municipalities therefore combine high vulnerability with robustly high pressure (probability of at least 80%): Igarapé-Miri, Cametá, Portel and Breves. This group does not depend on the exact threshold. The same four municipalities qualify with any threshold from 60% to 80%. Breves drops out at 85%, Portel at 90% and Cametá at 95%, leaving Igarapé-Miri alone. With cut-offs at the upper terciles, only Portel and Igarapé-Miri remain in the high-pressure and high-vulnerability group, and neither has a station; Cametá and Breves qualify under the median cut-off.

The QUALIÁGUA database has 31 stations and 485 samples in the study area, in eight municipalities. Seven are the municipalities with ANA stations. The eighth is Santo Antônio do Tauá, where one state station (Santa Terezinha) was sampled eight times between 2022 and 2024 but is not listed in the ANA inventory; it does not change Tiers 1 to 3. Measured quality showed no consistent association with the index (Online Resource 1, Table S7). At the municipal level ($n = 8$), the correlation between the APEI and the share of samples above a class 2 limit was -0.33, and that between the sanitation deficit and median thermotolerant coliforms was -0.54. At the station level ($n = 31$), the APEI and the exceedance share were unrelated ($\rho = -0.09$). Belém and Benevides, with low percentage sanitation deficits, had high coliform counts, because their stations are on urban streams. Most exceedances came from low pH and low dissolved oxygen, which also occur naturally in Amazonian waters.

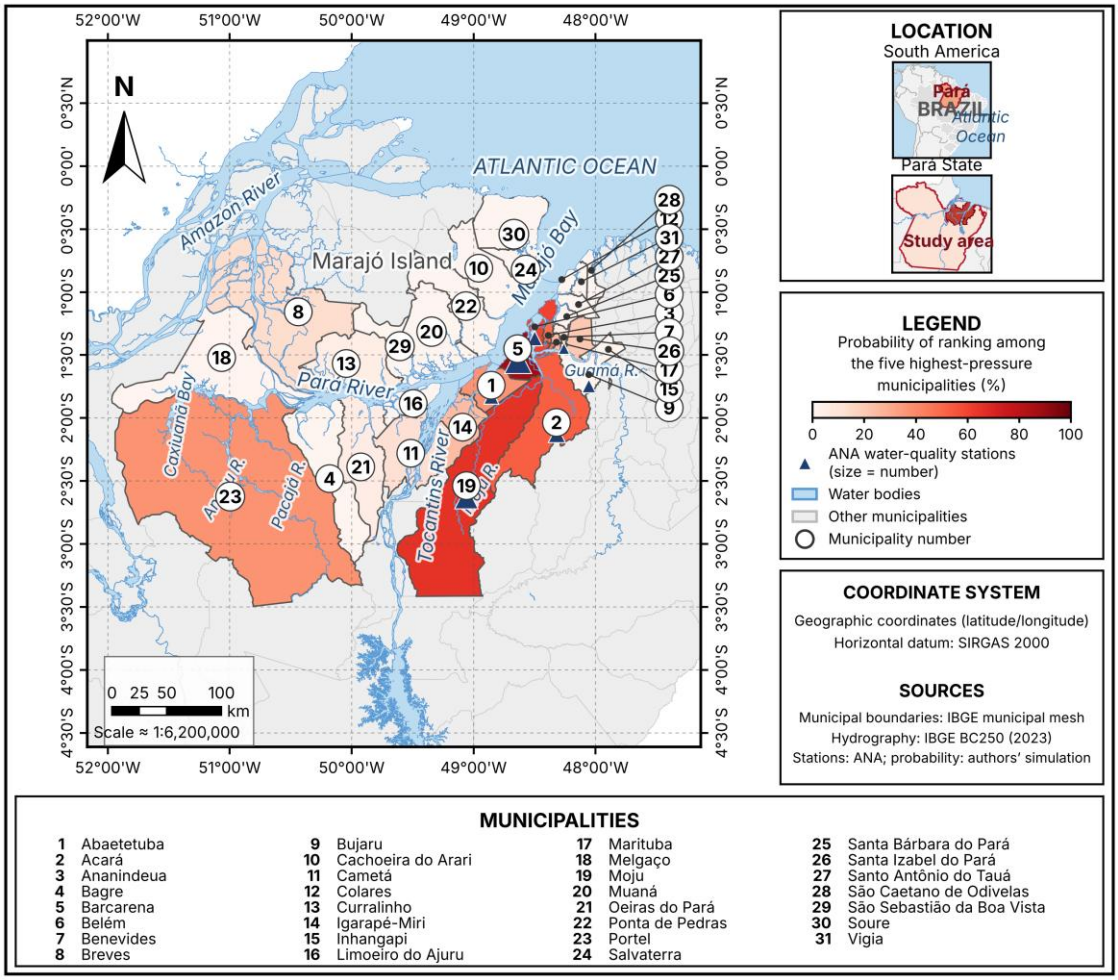


Fig. 7 Probability of ranking among the five highest-pressure municipalities (5,000 Monte Carlo draws) and location of ANA water-quality stations in operation. Triangle size is proportional to the number of stations. Numbers follow the key in Fig. 1

3.7 What is gained by following the priority rule

The seven monitored municipalities hold 55.0% of the population of the area but only 39.8% of the people without adequate sewage (Table 4). Among the 16 municipalities with high vulnerability, only Bujaru has a station, and only 2.8% of the people without adequate sewage in those municipalities live where water quality is monitored.

Table 4 Coverage of the monitoring network now and after adding one station per municipality under three allocation rules and the area optimum. Mun.: municipalities with a station; Pop.: population; No sewage: people without adequate sewage; HV mun.: municipalities with

vulnerability at or above the median that have a station; No sewage HV: people without adequate sewage in those 16 municipalities. All shares are percentages of the respective totals

Scenario	Mun.	Pop. (%)	No sewage (%)	Area (%)	HV mun.	No sewage HV (%)
Current network	7	55.0	39.8	19.0	1 of 16	2.8
Priority, 4 new	11	66.1	60.1	59.9	5 of 16	56.4
Pressure, 4 new	11	75.3	57.7	47.9	3 of 16	19.9
Population, 4 new[a]	11	79.9	65.2	32.2	3 of 16	39.4
Max. area, 4 new[b]	11	62.0	53.3	66.1	5 of 16	38.6
Priority or pressure, 8 new	15	87.5	78.9	61.3	5 of 16	56.4

[a] The same four municipalities (Ananindeua, Cametá, Marituba and Breves) maximise the share of people without adequate sewage. [b] Portel, Breves, Melgaço and Bagre.

Four new stations placed by the priority rule, in Igarapé-Miri, Cametá, Portel and Breves, raise the last figure from 2.8% to 56.4%. The same four stations placed by pressure alone raise it to 19.9%, and placed by population alone to 39.4%. The population rule covers more people in total (79.9% against 66.1%), because it selects Ananindeua and Marituba, but it reaches fewer of the people who combine exposure with vulnerability. With eight new stations the priority rule (Tiers 1 and 3) and the pressure rule select the same municipalities. The order of expansion therefore matters most when few stations can be added, which is the usual situation.

The priority rule is not the optimum of any single metric, and it should not be. The optimum for people without adequate sewage reaches 65.2% of them, against 60.1% for the priority rule, and the optimum for area reaches 66.1% of the territory, against 59.9%. The priority rule comes within about six points of both optima while reaching far more of the people who combine exposure with vulnerability (56.4%, against 39.4% and 38.6%). It is a compromise between metrics, and the area metric, which does not use the index, confirms that it does not simply reproduce the APEI.

4 Discussion

4.1 A robust ranking at the top

The first objective was to rank anthropogenic pressure from public data. The result is consistent with what is known about the estuary. Barcarena, with its port and industrial complex, leads

under four of the five weighting schemes and all three methods, and is second under the land-use focus, and published field studies have documented contamination and ecological change there (de Oliveira et al., 2020; Almeida Pinto et al., 2021; Gomes et al., 2021). The index adds a ranking in which Barcarena can be compared with 30 other municipalities on the same scale, and it shows that the leading position is not an artefact of one particular choice of weights.

The second objective was to test robustness. The top of the ranking (Barcarena, Moju and Acará) was stable across five weighting schemes, three aggregation methods and 5,000 random weight vectors, while mid-ranking positions were not, and the top survived a joint analysis in which the data treatment and the set of indicators also varied. This level of stability is not guaranteed in composite indicators (Saisana et al., 2005; Greco et al., 2019). It follows here from the structure of the data: municipalities at the top score high on at least two weakly correlated dimensions, so no single weight removes them. The exception is instructive. Belém and Ananindeua have high scores only on the demographic and economic dimensions, which are strongly correlated (0.804). Their rank intervals are therefore wide. Reporting rank intervals, and not only scores, makes this difference visible.

The tests also show the limit of the index. Its ranking depends on the decision to measure total load and not intensity. Per unit of area, the metropolitan municipalities come first and the large land-use municipalities fall. Neither version is wrong. They answer different questions, and the choice should follow the use. For allocating sampling points among municipalities, total load is the appropriate basis, because stations are counted per municipality and a larger load spread over a larger territory needs more points to be detected. For comparing how stressed a given stretch of shoreline is, intensity is. The two versions agree on the leader (Barcarena) and differ on the large rural municipalities, so a manager who adopts the intensity view should read the metropolitan tier (Tier 3) as the first priority.

The behaviour of entropy weights deserves a note of caution. Entropy assigned almost half of the weight to the economic dimension, simply because port cargo and exports are concentrated in a few municipalities. This is the kind of result that Zhe et al. (2021) describe as abnormal in water-quality applications. Dispersion is not the same as importance (Becker et al., 2017). We kept entropy as a scenario because it is widely used, but we do not recommend it as the baseline for a pressure index.

4.2 Three kinds of pressure, three kinds of monitoring

The pressure profiles have a direct use in sampling design. A single list of parameters applied to the whole estuary would be inefficient. In the urban-industrial and port profile, the main concerns are metals, hydrocarbons and industrial effluents, and these are the parameters that monitoring around the Barcarena industrial complex has addressed (Almeida Pinto et al., 2021). In the land-use frontier, the pressures are deforestation, cattle and crops, and the relevant parameters are sediments, nutrients and pesticides. In the riverine profile, the dominant pressure is the lack of sewage collection, and the priority parameters are microbiological indicators, organic load and nutrients. Water quality index models can combine such parameters, but they also carry uncertainty from parameter selection and weighting (Uddin et al., 2021). Matching parameters to the pressure profile is a simple way to reduce that uncertainty.

4.3 Monitoring gaps and equity

The third objective was to compare pressure with the monitoring network. The network is concentrated: seven municipalities hold all 31 stations, and Barcarena and Moju together hold 18. This concentration is partly justified, because these are high-pressure municipalities. But the correlation between stations and pressure (0.61) leaves a large unmonitored area. More than half of the municipalities with above-median pressure have no station.

The risk matrix shows that the gap is not neutral with respect to people. Five of the six municipalities that combine high pressure and high social vulnerability are unmonitored. In Portel, Breves, Igarapé-Miri, Oeiras do Pará and Cametá, a large share of households lacks sewage collection and piped water, and child mortality is higher (Table 1 indicators; IPS Brasil, 2026). These are the places where poor water quality is most likely to become a health problem and where it is least likely to be detected. This pattern matches the concern that the benefits and burdens of coastal development are unevenly shared (Bennett et al., 2021).

A decision rule follows for the allocation of new sampling points (Table 5). The first points should go to the unmonitored municipalities where high vulnerability meets robustly high pressure: Igarapé-Miri, Cametá, Portel and Breves. Oeiras do Pará belongs to the same group in the baseline, but its pressure is above the median in only 42% of the runs, so it should be confirmed in the field first. A third tier includes Santa Izabel do Pará, Ananindeua, Marituba and

Vigia, which have high pressure but lower vulnerability and are close to Belém. The riverine municipalities with low pressure and high vulnerability form a fourth tier, in which the main parameter of interest is microbiological quality. The 80% threshold is a convention, and the probabilities are reported so that a manager can move it.

Table 5 Priority tiers for the expansion of water-quality monitoring

Tier	Rule	Municipalities (probability of above-median pressure, %)	Suggested action
1. Monitor first	No station, high vulnerability, P ≥ 80%	Igarapé-Miri (100), Cametá (91), Portel (89), Breves (80.3)	Install a station, with the parameters of the pressure profile. The gap holds in at least 80% of the 10,000 runs that vary weights, data treatment and indicator set.
2. Confirm in the field	No station, high vulnerability, P < 80%	Oeiras do Pará (42)	Exploratory sampling before committing a permanent station.
3. Extend the metropolitan network	No station, pressure above the median, lower vulnerability	Santa Izabel do Pará (97), Vigia (70), Ananindeua (67), Marituba (65)	Extend the existing network around Belém.
4. Sanitation surveillance	No station, pressure below the median, high vulnerability	Ten municipalities, among them Curralinho, Melgaço and Bagre	Periodic microbiological sampling, linked to health surveillance.

The 2,001-point grid of the project allows this allocation to be refined within each municipality in a later step.

4.4 Comparison with other approaches

Most approaches to monitoring network design start from water-quality data or hydrodynamic models and optimise station locations for information content or representativeness (Jiang et al., 2020; Kim & Hwang, 2020; Alvarez-Vázquez et al., 2023). The same holds for studies that rationalise existing networks with multivariate statistics or neural networks (Villas-Boas et al., 2017; Calazans et al., 2018), which need long series of measurements. These methods give precise answers where data exist. In the Amazon estuary they face a circular problem, because the data needed to design the network are the data the network is supposed to produce. A pressure index breaks this circle. It uses information that already exists for every municipality and gives a first stratification of the territory, on which more detailed designs can later be built.

The approach also differs from global cumulative impact maps (Halpern et al., 2019). Those maps work on regular grids, with ecosystem-specific vulnerability weights, and they are designed

for comparisons between regions. A municipal index has coarser spatial resolution, but it matches the scale at which sanitation, land-use and licensing decisions are made in Brazil. It also uses variables, such as sewage coverage from the census, that global products do not include. The two scales are complementary. In the project of which this study is part, the municipal index sets priorities between municipalities, and the 2.2 km grid sets sampling points within them.

Finally, the explicit treatment of weight uncertainty distinguishes the index from many environmental composite indicators, which report a single ranking under a single set of weights. The probability of ranking among the five highest-pressure municipalities (Fig. 7) is easy to communicate to managers and is more informative than a score with three decimal places.

4.5 Limitations

Several limitations should be kept in mind. First, the index measures potential pressure from secondary data, not measured loads or water quality. It indicates where to look, and it does not replace sampling. Second, supply chains enter only through proxies, such as industrial value added, exports, industrial jobs and port cargo. The origin, destination and route of the açaí, fish, timber, mining, oil palm and fuel chains were not measured. Third, port cargo covers only the public ports managed by CDP. Private terminals enter as zero. For Barcarena this does not matter, because its score is already at the upper limit, but it could underestimate a municipality with private terminals and no public port. Fourth, the sources do not separate missing records from true zeros. The sensitivity test bounds this effect ($\rho \geq 0.956$), but under-reporting cannot be ruled out. Fifth, the municipal scale hides variation within municipalities, which is large in Portel and Breves. Sixth, the vulnerability dimension has only three indicators, and the three pressure profiles overlap and are only moderately stable under resampling. Seventh, the index mixes municipal totals with a few rates, counts population twice and behaves as a measure of total load, so its ranking changes when magnitudes are expressed per unit area. Eighth, the municipality is an administrative unit, not a hydrological one. The index does not represent how much of each municipality drains to the estuary or how pressure is transported by tides and river flow. The distance-decay variant is only a first approximation to connectivity, and it kept the top of the ranking and the first tier unchanged. Finally, the thematic weights were not validated with managers or communities, and the index could not be validated against measured water quality. The only open data cover eight municipalities, and the exploratory comparison showed no

consistent association. This is expected, because each station records the dilution and tidal conditions of one site, and a few stations cannot represent municipalities of thousands of square kilometres. A proper test needs sampling designed for that purpose, which is the aim of the project's field campaigns. The index should be read as a screening of potential pressure.

These limits define what the index should not be used for. It is not evidence that a municipality pollutes, and it should not be used in licensing, enforcement or the allocation of fines. It does not estimate health risk or exposure, so it cannot replace epidemiological surveillance. It does not rank the performance of municipal governments, and it should not by itself decide the transfer of sanitation funds. Its legitimate use is narrower: to decide where measurements are taken first, and with which parameters.

4.6 Implications for public policy

The results suggest three actions for the agencies responsible for water resources and sanitation in the estuary. The first is to extend water-quality monitoring to the western and southern margins, starting with Igarapé-Miri, Cametá, Portel and Breves, and to confirm Oeiras do Pará in the field. The second is to adapt the monitored parameters to the dominant pressure profile of each municipality. The third is to treat the sanitation deficit as the most widespread pressure in the estuary. Its score is 0.5 or higher in 18 of the 31 municipalities, more than any other pressure dimension, it affects both the pressure and the vulnerability sides of the risk matrix, and it is the dimension most directly within the reach of municipal and state policy under the new legal framework for sanitation (de Oliveira et al., 2027).

The allocation exercise gives the size of the gain. Four stations placed by the priority rule would take the share of people without adequate sewage in high-vulnerability municipalities who live where water is monitored from 2.8% to 56.4%, more than the same four stations placed by pressure or by population alone.

These actions have a common basis in equity. A monitoring network that follows only industrial and port activity protects the places where pressure is visible and regulated, and leaves out the places where people drink, fish and bathe in untreated water. In highly vulnerable regions, the absence of data is itself a policy problem, because contamination that is not measured does not enter licensing, sanitation planning or health surveillance. A pressure and vulnerability index is a

low-cost way to correct that bias before measurements exist. It needs only public data and free software, so state environmental agencies and river basin committees can update it every year and use it to justify the location of new stations to oversight bodies and to the communities involved. The same logic applies to other estuaries and river basins of the Global South, where monitoring budgets are small and the territory is large.

4.7 Next steps

Water-quality data from field campaigns can later be compared with the index at the scale of sampling points, not of municipal averages. Stakeholder weights can be elicited with structured and participatory multicriteria methods (Scheili et al., 2020), and flow data on supply chains can replace the current proxies. Because the index uses only public data and open code, it can be updated yearly and applied to other data-poor estuaries.

5 Conclusions

The study met its three objectives with a screening and allocation protocol built only from public data. The municipal index ranked anthropogenic pressure in the Marajó Bay estuary with a stable top (Barcarena, Moju and Acará) across five weighting schemes, three aggregation methods, random weights, data treatments, missing-value and connectivity variants, whereas mid-ranking positions depend on the modelling choices. Crossing pressure with social vulnerability and with the station network turned the ranking into a priority list. The current network is concentrated in seven municipalities and leaves unmonitored nine of the 16 high-pressure municipalities and five of the six that combine high pressure with high vulnerability.

The main contribution is the protocol itself: a transparent sequence of index, uncertainty analysis, risk matrix and allocation rule that tells an agency where to measure first, how robust that choice is and what it gains. Four stations placed by the rule, in Igarapé-Miri, Cametá, Portel and Breves, would raise the share of people without adequate sewage in high-vulnerability municipalities who live where water quality is monitored from 2.8% to 56.4%, within about six points of the optima for total sewage deficit and for area. The three pressure profiles indicate which parameters to measure in each place, and the sanitation deficit emerges as the most widespread pressure and the one most within reach of municipal and state policy. Because the protocol needs only public data

and open code, state agencies, river basin committees and public universities that run field campaigns can update it every year and use it to justify the location of new stations.

The results hold under stated boundary conditions. The index measures potential total load at the municipal scale, not measured water quality, intensity or hydrological transport, and the open state water-quality data, available for only eight municipalities, could not validate it. It should not be used for licensing, enforcement or the allocation of funds. Future work should compare the index with the water-quality campaigns of the project at the scale of sampling points, elicit weights from managers and communities, replace the supply-chain proxies with flow data and refine the allocation within municipalities. A further step is to treat the choice of new stations as a value-of-information problem, in which each candidate site is valued by how much its measurements are expected to change management decisions, so that the protocol moves from screening to the explicit optimisation of the monitoring budget.

Statements and Declarations

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Code availability The Python code that reproduces all results, tables and figures is available at https://doi.org/10.17605/OSF.IO/JWA4P.

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