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Assessing ecosystem services provision using Bayesian Belief Network in Southern Europe marine forests

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ABSTRACT

Marine forests are vital ecosystems that underpin biodiversity and human well-being. Despite their ecological significance, these habitats remain underrepresented in policy frameworks and are increasingly threatened by anthropogenic pressures. Effective conservation and restoration efforts require a system-level understanding of the dynamic interactions between human activities and ecological components.

We use Bayesian Belief Networks to simulate and predict changes in ecosystem service provision within southern European marine forests, with a focus on the continental Portuguese coast. Our approach integrates field measurements and expert knowledge to assess how shifts in anthropogenic drivers and biological components affect ecosystem functionality in data-limited settings. Major concerns include climate-driven herbivory, invasive species patterns, and their combined impact with other existing drivers. Nonetheless, results indicate restoration initiatives could enhance ecosystem services provision by up to 40 percentage points. Availability, reliability, and size of observations significantly influenced the choice between expert-based data and field measurements. The findings provide an initial step toward applying a Bayesian Network approach to assess ecosystem service provision in European marine forests and evaluating the potential benefits of restoration interventions. This work identifies key leverage points for enhancing ecosystem resilience and offers a decision-support tool to inform targeted conservation strategies across southern European coastal regions.

1. Introduction

Coastal ecosystems rank among the most productive in the marine realm, delivering a wide array of ecosystem services (ES) essential to human well-being, including food provision, climate regulation, and cultural identity (Barbier, 2012; Galparsoro et al., 2021; Pinsky et al., 2018; Varkey et al., 2013; Wyatt et al., 2017). Habitats such as kelp forests and seagrass meadows are key foundation ecosystems, particularly in temperate latitudes (Cabaço and Santos, 2007; Cunha et al., 2013; Wernberg et al., 2019). These habitats support marine biodiversity by offering nursery grounds, foraging areas, and water purification functions (Castro et al., 2019; Cunha et al., 2005; de los Santos et al., 2020; Duarte et al., 2022; Eger et al., 2023). In addition to their ecological importance, they also provide direct and indirect benefits to human societies, such as nutritional resources (Pacheco et al., 2021) and significant potential for carbon sequestration (Filbee-Dexter et al., 2024; Franco et al., 2025; Martins et al., 2022; Sousa et al., 2019). However, these ecosystems are increasingly threatened by anthropogenic activities including coastal development, overfishing, and climate change (de los Santos et al., 2019; Nichols et al., 2019; Wernberg et al., 2019). These threats compromise their capacity to maintain essential ES (Aps et al., 2018; Cardoso et al., 2008; Ehler, 2021; Varkey et al., 2013) which underscores the urgent need for evidence-based conservation and restoration actions (Duarte et al., 2022; Nichols et al., 2019).

Across Europe, kelp forests have shown a general decline in native species abundance, while seagrass meadows – despite signs of recent recovery – remain vulnerable to cumulative stressors (Araújo et al., 2016; de los Santos et al., 2019). In continental Portugal, similar patterns have emerged. Marine forest species are experiencing both population declines and distributional shifts. Native kelp species have

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retreated from southern regions, now largely restricted to cooler northwestern coasts (Araújo et al., 2016; Tuya et al., 2012). At the same time, seagrass meadows face persistent challenges due to the interplay of environmental and anthropogenic drivers (Cabaço and Santos, 2014; Cunha et al., 2013). These trends point to the necessity of targeted interventions that not only preserve these ecosystems but also secure the ecosystem services they sustain. Such strategies demand system-level understanding of the relationships between abiotic and biotic components, and the ES they support (Mitchell et al., 2024; Pérez-Miñana, 2016).

There is currently limited understanding of the complex mechanisms that underlie ES provision, leading to several methodological challenges (Pascual et al., 2016; Rettig et al., 2023). This calls for novel, integrative modelling approaches capable of accommodating limited data and high uncertainty (Carriger et al., 2019; Pérez-Miñana, 2016).

Bayesian Belief Networks (BBNs) have emerged as promising tools in this regard, owing to their capacity to synthesize diverse data sources while explicitly handling uncertainty (Pascual et al., 2016; Pérez-Miñana, 2016; Tang et al., 2019). Originally developed in fields such as medicine and machine learning, BBNs have been applied to ecological and ES assessments (Höfer et al., 2020; Tang et al., 2019). Their flexibility enables researchers to identify probabilistic relationships amongst variables – including empirical data and experts' knowledge (Laurila-Pant et al., 2019; Pascual et al., 2016; Pham et al., 2021) – offering valuable insights into dynamics governing ES outcomes (Carriger et al., 2019; Gacutan et al., 2019; Höfer et al., 2020; Scrieciu et al., 2021; Wu et al., 2018).

This study aims to evaluate how marine forests contribute to ecosystem services provision under shifting anthropogenic pressures using a BBN approach along the continental Portuguese coast. This region lies within the South European Atlantic Shelf ecoregion and represents a transitional marine zone where species of both boreal and Lusitanian origin coexist. A significant number of cold- and warm-water species reach their southern or northern distributional limits along this coastline, making it a biogeographic boundary highly sensitive to climate-driven shifts in species composition and ecosystem function (Tuya et al., 2012). In addition, considering the Post-2020 Global Biodiversity Framework targets (Convention on Biological Diversity, 2022) and recent restoration initiatives in southern Europe, this case study can provide valuable information for future conservation efforts (Eger et al., 2024, 2022; European Commission, 2025).

To the best of our knowledge, this is the first study to apply BBNs to assess ES in southern European marine forests. Our model integrates field measurements and expert-based knowledge to assess the capacity of these ecosystems to deliver key services. The results offer foundational insights for policy development, informed management, and future research. Furthermore, this work provides the groundwork for evaluating the economic value of marine forests, supporting cost-benefit analysis essential for advancing sustainable conservation and restoration efforts in the region.

2. Methods

2.1. Study areas

The Portuguese coast, spanning over 800 km, constitutes a significant transitional zone between warm-temperate and cold-temperate species in the Northeastern Atlantic. Northern regions are characterized by kelp forests, dominated by species such as *Saccorhiza polyschides*, *Laminaria hyperborea,* and *Laminaria ochroleuca* (Tuya et al., 2012). These habitats thrive on reefs interspersed among sandy beaches within both the intertidal and shallow subtidal zones. As the coastline predominantly follows a rectilinear north–south orientation, kelp abundance decreases markedly from central Portugal towards the south, where it becomes nearly absent (Tuya et al., 2012). In contrast, marine forests on the southern coast are dominated by seagrasses, specifically three of Europe's four native seagrass species – *Cymodocea nodosa*, *Zostera marina*, and *Zostera noltii* – all of which are indigenous to the Portuguese coast (Cunha et al., 2013).

Ria Formosa, located in southern Portugal, is a mesotidal lagoon known for its distinctive features and prevalence of seagrasses (Cunha et al., 2013; Erzini et al., 2022). It encompasses a network of inlets, sand barrier islands, and salt marshes, contributing to its unique ecological composition. The lagoon is home to two emblematic species – the long-snouted seahorse (*Hippocampus guttulatus*) and the short-snouted seahorse (*Hippocampus hippocampus*) – enhancing its ecological significance (Correia, 2022). Our study examines the factors driving ES provision by kelp forests along Portugal's western coast – specifically in the northern (*Viana do Castelo*), central (*Peniche*), and southern (*Sines*) regions – and by seagrass meadows along the southern coast, particularly in the *Ria Formosa* lagoon (see Fig. 1).

2.2. Systems characterization

To construct the BBNs, we have carefully analysed the relevant links responsible for the provision of ES by marine forests. Hence, we have implemented a search in the Web of Science platform (Clarivate, 2023) to first identify linkages between the drivers affecting the condition of kelp forests and seagrass meadows, and how these influence the provision of ES.

Our review focused on two primary objectives: (i) collecting publications identifying the ES provided by marine forests (cf. CICES, 2018), and (ii) collecting publications with substantial data on the drivers responsible for marine forests' condition. This process involved retrieving publications most related to our targeted species. To complement this review, we engaged with experts from the BlueForests project and considered additional articles suggested by them. This collaborative effort resulted in the screening of 2,200 articles published until 2022, with 127 articles ultimately meeting our eligibility criteria. Using NVivo software (Lumivero, 2023), we analysed the selected articles ending up with 80 articles that contributed valuable insights into the development of our first conceptual diagrams (*i.e.,* one for kelp and one for seagrasses). For a detailed breakdown of our review, including identification, screening, and eligibility, please see the Supplementary Materials.

2.3. Bayesian Belief networks

BBNs are statistical tools designed to represent complex systems, capturing the ecological relationships within them (Marcot et al., 2006; Pham et al., 2021). As graphical models, BBNs establish links between actions and outcomes by considering the joint probability of different variables (Yuniarti et al., 2021). BBNs consist of two essential components – a directed acyclic graph (DAG) and conditional probability tables (CPTs) – which represent causal relationships among nodes (Landuyt et al., 2013; Owusu et al., 2022; Pearl, 1986). In the DAG, arrows indicate directed relationships from parent nodes to child nodes. The CPTs contain the conditional probability distributions of each child node's possible states, given the state of its corresponding parent node. The distributions of child nodes are estimated using *Bayes*' theorem (Neapolitan, 2004; Pearl, 1986):

$$P(x|y) = \frac{P(y|x)P(x)}{P(y)} \tag{1}$$

Here $P(x)$ and $P(y)$ are the marginal probabilities of observing x and y, respectively. $P(x|y)$ is the conditional probability of x given y, and $P(y|x)$ is the conditional probability of y given x, where y represents the parent node and x the child node.

To preserve consistent probabilistic relationships among variables, we developed separate networks for each type of marine forest (Neapolitan, 2004). We used the *bnlearn* package in *RStudio* and *Netica*

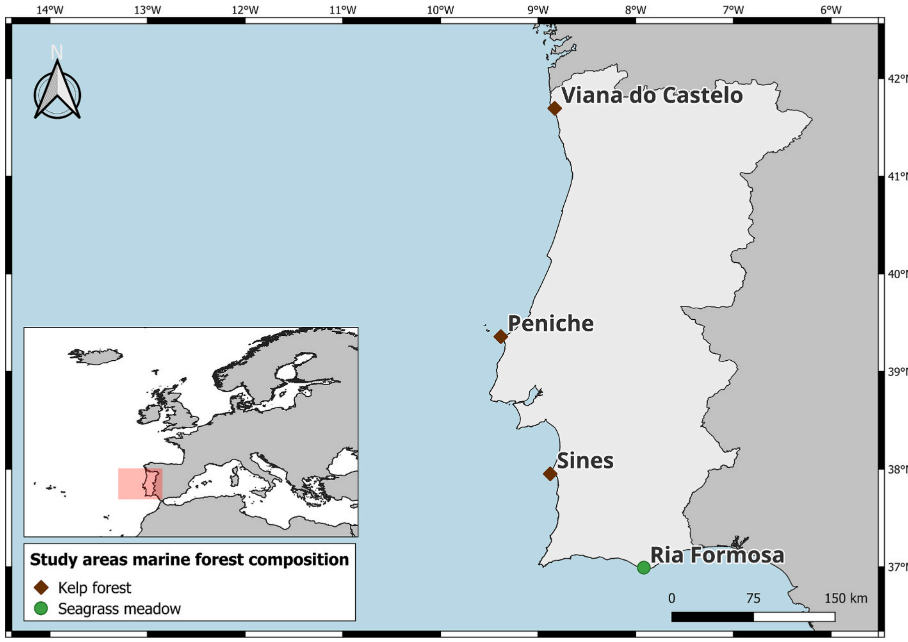

Fig. 1. Study areas marine forest composition. Information on the type of marine forest (*i.e.,* kelp forest or seagrass meadow) in each selected location. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

software (Norsys Software Corp., 2024; Scutari, 2010) to implement the models.

To capture the dynamics of ES provision in Portuguese marine forests, we began by constructing DAGs for each BBN (see Fig. A1 in the supplementary materials). During this process, a series of online meetings was conducted with two project collaborators who have extensive expertise in marine forests in our study areas. These consultations provided interesting insights into key variable interactions and supported informed assessments of ES. Following these meetings, we refined each DAG to support the estimation of CPTs. Conditional probabilities were informed by both field measurements and expert input. To guarantee a thorough analysis, we use both experts-based and field-measurement data. Collection methods for both sources are described in the next two subsections.

2.4. Expert-Based survey

2.4.1. Survey Design

In December 2023, we conducted a survey to be delivered to the scientific community. The survey questions were tailored to each BBN, resulting in two different versions of the survey: one for kelp forests and another for seagrass meadows. Our sample comprised experts who have made significant contributions to marine forest research in Portugal, especially in our study areas.

The survey was divided into three main sections:

I. Drivers, where we assessed expert perceptions of the prevalence of drivers in the selected areas;
II. Marine Forests' Condition, where we elicited conditional probabilities of marine forests conditions given the state of the drivers;
III. Ecosystem Services, where we assessed the provision level of ES given the marine forests' condition state.

The condition of marine forests was categorized into three levels: *Good*, *Average*, and *Poor*. These levels were defined as follows: *Good* condition – Marine forests are intact and capable of delivering most ES; *Average* condition – Forests show localized degradation affecting some ES; *Poor* condition – Extensive degradation significantly compromises ES provision.

Each survey's question included a defined degree of confidence in the answer provided (from 0 to 10). The confidentiality of each respondent was guaranteed.

We collected data from nine experts, including three on kelp forests and six on seagrass meadows. Seagrass experts provided information for supporting seagrass BBN for *R. Formosa*, while kelp experts provided insights for the three Kelp BBNs (*i.e., Viana do Castelo, Peniche and Sines*). Experts from the kelp survey responded only to the sections linked to their respective working areas. While the disparity in the number of experts may raise concerns over the comparison or generalization of results across kelp and seagrass, it's important to keep in mind that while we are restricted to the number of available experts, they have substantial knowledge of the study areas which is not available anywhere else.

Data were used to estimate the conditional probabilities and to map the relationship between drivers, marine forests, and ES provision. Table 1 describes the drivers and ecosystem services related to Portuguese marine forest habitats (for more information see Table A4 and A5 in the supplementary materials).

2.4.2. Conditional probabilities of the Expert-Based survey

In the survey, respondents were asked to assess not only the likelihood of each state of the drivers occurring but also the likelihood of kelp or seagrass being in condition *i*, given that driver *X* is in state *j*. For example, we asked for the likelihood of burial activities being "*high*" and the probability of kelp being in the state *Good* given that burial activities were in the state "*high*". Respondents were also asked about the likelihood of ES being in state *k* given the state *i* of marine forests. To find the conditional probabilities at each node, we aggregated the results from the survey. For this aggregation, we obtained a weighted average of each probability across all respondents. This weight was estimated using the degree of confidence per answer (numerical range from 0 to 10). Higher confidence responses yield higher weight, and vice versa. Using *RStudio*, we estimated the conditional joint probabilities of each state at each node with the weighted averages of each response.

We estimated joint probabilities for four different settings: kelp forests in *V. Castelo*, *Peniche,* and *Sines*, and seagrass meadows for *Ria Formosa*. Considering the number of variables and limited data availability, we followed a *Naïve Bayes*-like approach to learn the joint conditional probabilities.

Table 1
Key Components Influencing Marine Forests' Provision along the Portuguese Coast. Includes information on the drivers influencing marine forest conditions, and details the services offered by marine forests in the selected study areas.

Kelp forests Driver	Description
Invasive Species	Abundance of invasive species *Asparagopsis armata* in the selected areas.
Bottom Trawling	Activities involving bottom trawling in the selected areas.
Burial	Events that result in the burial of kelp in the selected areas (*e.g.,* dredging activities).
Diseases	Prevalence of infectious diseases affecting kelp in the selected areas.
Extreme Events	Predisposition to the occurrence of stormy events in the selected areas.
Grazers	Grazer's predation in the selected areas.
Water Turbidity	Water conditions responsible for influencing light availability in the selected areas.
Water Temperature	Water temperature in the selected areas (marine heat waves included).
Ecosystem Services	
Aquaculture Potential	Utilization of kelp for food and alginate production.
Biodiversity	Abundance of non-commercial species around kelp.
Carbon Sequestration	The capacity of kelp to sequester carbon.
Health Benefits	Utilization of kelp-based compounds for the production of health products.
Nursery Areas	Abundance of commercial species around kelp.
Water Purification	The ability of kelp to improve water conditions.
Seagrass meadows	
Driver	**Description**
Invasive Species	Abundance of invasive species such as *Caulerpa prolifera* or *Asparagopsis armata*.
Burial	Events that result in the burial of seagrass meadows (*e.g.,* dredging activities).
Fishing Activities	Disturbances caused by the fishing methods used in the area (*e.g.,* digging for clams, use of trawl, or seine nets)
Eutrophication	Anthropogenic nutrient disturbance in the selected areas.
Extreme Events	Predisposition to the occurrence of stormy events in the selected areas.
Grazers	Abundance of grazers in the selected areas, for example, mesograzers or the fish *Sarpa salpa.*
Water Turbidity	Water conditions responsible for influencing light availability in the selected areas.
Water temperature	Water temperature in the selected areas (marine heat waves included).
Ecosystem Services	
Biodiversity	Abundance of non-commercial species around seagrasses.
Carbon Sequestration	The capacity of seagrasses to sequester carbon.
Emblematic Species	Abundance of emblematic species (*e.g.,* seahorses) around seagrasses.
Erosion Control	Seagrasses capacity for sediment stabilisation.
Nursery Areas	Abundance of commercial species around seagrasses.
Water Purification	The ability of seagrasses to improve water conditions.

To estimate the unknown Conditional Probability $P(Marineforests = state_i | X_n = state_j)$, in which X_n, is the n-dimensional vector of drivers affecting kelp and seagrass, we relied on multiple assumptions. First, we took the probabilities of the states of each of the drivers, including those that are not independent, as given, which allowed us to state that invasive species and grazers are conditionally independent given water temperature. Thus, the effect of water temperature in marine forests through invasive species and grazers is already accounted for in those two drivers. This was possible as the data for the probabilities of each state of these nodes, given water temperature, was available from the expert-based survey. Secondly, we also assumed conditional independence across all other drivers. Thus, using the expert-based data on the state of marine forests given each parent node, we estimated the conditional probabilities of each state i of the marine forests given the state j of all its parent nodes through expression (2). Then, together with the conditional probabilities of each state of ES given marine forests, also provided by the experts, we used the *Netica* open version software to complete each BBN.

$$P(Marineforests = state_i | X_n = state_j) = \prod_{l=1}^{n} P(Marineforests = state_i | X_l = state_j) \tag{2}$$

2.4.3. Ecosystem services provision scenario analysis

After the completion of each BBN, we designed four hypothetical scenarios (three pessimistic and one optimistic). These scenarios were developed to estimate the combined effects of different drivers on the provision of ES by marine forests. Table 2 compiles relevant information regarding each scenario.

2.5. Field measurements

In addition to the expert-based data, we used field measurements on kelp forests to estimate a reduced-form Kelp BBN. Essential information on parameters driving kelp occurrence was obtained from available field records and unpublished datasets accessed upon request, covering the *Viana do Castelo*, *Sines*, and *Peniche* sites along the Portuguese coast. The compiled dataset spans 2011–2020 and includes kelp abundance and species composition, as well as the biological and environmental drivers affecting condition (*e.g.,* water temperature, light availability, grazers abundance). From these data, we estimated the conditional probabilities of a reduced-form BBN and compared them with those derived from the expert-based BBN to assess the value of expert-based knowledge in a data-limited context. Because observations of seagrass meadows in *Ria Formosa* were not available for the identified drivers, a reduced-form Seagrass BBN was not considered.

2.5.1. Model estimation

We estimated the parameters of a simplified Bayesian Network using available field measurements. Data on kelp populations, grazers abundance, mean fetch,[1] water turbidity,[2] seawater temperature, and

[1] Mean fetch was used to assess exposure to wind and waves.
[2] Water turbidity was used as a proxy for underwater light availability for photosynthesis.

Table 2
Scenarios used for ecosystem provision analysis.

Scenario	Description
Climate Change	Given that climate change will continue to influence ocean conditions (Alexander et al., 2020; Hand et al., 2019) and the frequency of extreme events such as storms, floods, and marine heat waves (Smale et al., 2019; Swain et al., 2020), we consider for this scenario that is certain that water temperature and extreme events independent nodes will both be *"high"*. In our study, we consider water temperatures to be *"high"* for kelp areas with sea temperatures higher than 18 °C and seagrass areas with sea temperatures higher than 21 °C. These values represent observed thresholds for the species considered in the study. Except for water temperature, drivers' thresholds were qualitatively defined due to the lack of confidence demonstrated by project collaborators in asserting the state of drivers in a quantifiable way when developing the survey. These challenges were associated with the difficulty in obtaining appropriate metrics for our study areas considering data availability and complex system interactions. Further, they believed respondents would be more confident in providing answers if such states were qualitatively defined (for more information, see Table A4 and A5 in supplementary materials).
Human Pressures	Considering the effects of human disturbances in these habitats (Araújo et al., 2016; Cabaço et al., 2005; Cabaço and Santos, 2014) we simulate a scenario of consistently high anthropogenic disturbance. For kelp forests we consider the bottom trawling and burial nodes to be *"high"*. Regarding seagrass meadows we consider eutrophication, clam harvesting and burial nodes to be *"high"*. Differences in the drivers used for both habitats were related with the expert consultations on the most relevant drivers in kelp forests and seagrass meadows habitats.
Cumulative Impact	We define a scenario where all these identified drivers are considered to be *"high"* in our selected study areas. This scenario represents a worst-case cumulative impact scenario.
Conservation and Restoration Success	This scenario represents a hypothetical scenario of success from conservation and restoration initiatives that results in the best possible outcome for marine forests condition in our selected study areas. Further consultations with our project collaborators permitted to assess areas of interest for these initiatives in our study areas. To collaboratively delineate these areas, we considered experts ecological data and opinions, together with publicly available information on marine forests national important sites (Assis et al., 2011, 2009; Santos, R. et al., 2023).

upwelling intensity[3] were used; their structural representation, including node dependencies, is shown in Fig. 2. With a dataset of 750 observations, we aimed to minimize prediction error while fitting the model.

Existing methods to learn parameters from data in BBN require that the data be either continuous, discrete, or a mix of both. In mixed-type networks, parameter learning is not feasible when a parent node is discrete and the corresponding child node is continuous. To enable direct comparison with the expert-based model and address technical constraints, we discretized all variables in the dataset. We avoided imposing an arbitrary structure and instead designed an algorithm to optimize the discretization scheme based on model performance. This optimal number faces a trade-off between dimensionality and data availability. The larger the number of discrete states per variable, the better the model explains variations in the data and probabilities. However, the larger the number of parameters to estimate, the larger the required dataset to make estimation possible. We discretized each variable into between 2 and 5 bins using quantile-based discretization, resulting in 4096 distinct datasets representing all possible combinations of different intervals per variable. Each variable was discretized using the *quantile* discretization method instead of the *interval* method. This allows us to group the variables' observations in a unique dataset based on the mass of the distribution of its values, rather than to use an arbitrary ad-hoc interval to be defined by the researchers.

For each dataset, we used two parameter learning algorithms. We applied both *Bayesian Posterior Estimation (Bayes)* and *Maximum Likelihood Estimation (MLE)* using the *bnlearn* package in *RStudio*. In total, we estimated parameters for 8192 different BBNs. To understand which model would perform better, we implemented a *k*-fold validation test.

In this test, we have split the dataset into a test and a training dataset. The train dataset is then split into *k* sub-samples of equal size. The first sub-sample of size *n/k* is set aside, and the model is reparametrized using the remaining subsamples. Model predictions for the validation fold were compared to the actual outcomes in the test dataset, to assess predictive performance, while we extract the expected loss from the negative log-likelihood function. This is repeated for every *k* sub-sample, and we choose the best performing model based on the average expected loss across all the *k* sub-samples. As recommended by the literature (Marcot and Hanea, 2021), we perform this test using 10 subsamples, implementing it in each of the estimated 8192 models. The results are compared with the respective underlying model discretized dataset. To evaluate model robustness, we assessed whether the same performance metrics remained consistent across resampled datasets.

To assess the validity of the previous results, we resample (with replacement) the original dataset 100 times. We then test the resampled datasets to understand if they behave similarly to the original dataset. Fig. A5 in the supplementary materials suggests alignment between simulated and original distributions, showing a similar behaviour in the observations. For each of the 100 resampled datasets, we followed the approach defined previously, and, in total, we estimated 819,200 models, which were then tested using the same *k*-fold cross-validation test. This has increased very significantly the computational necessity of the code. A brief description of the computational needs is available in the GitHub repository of the code.

3. Results

3.1. Expert-based Bayesian Network

When examining the BBNs, it is evident that different environmental and social contexts yield different outputs to the condition of marine forests and related provision of ES. Fig. 3 illustrates the Kelp BBN estimation for the *V. Castelo* region, reflecting the relationships influencing marine forest provision under different pessimistic scenarios. In the *Climate Change* scenario, the kelp condition in *V. Castelo* is significantly affected by increased seawater temperature and the frequency of extreme events. This results in reduced probabilities of kelp being in *Good* condition, compared to its current state (Fig. 3 – A). Consequently, the cumulative effect of human pressures and climate change further accentuates these conditions, with the probability of a *Poor* kelp condition increasing from 3 % to 31 % (Fig. 3 A and D). Despite these challenges, experts believe that kelp forests in this region are most likely to remain in *Average* condition (*i.e.,* reflecting localized degradation which affects some ES provision). In *Peniche*, similar trends are observed with kelp forests achieving *Average* conditions (over 90 % confidence) across scenarios (see Fig. A2 in the supplementary materials). Still, depending on kelp forest location, ES provision estimates differ. For instance, in *V. Castelo*, biodiversity and health benefits provision are expected to be "low" in most pessimistic scenarios but "high" in its current state while in *Peniche,* biodiversity is expected to remain high and health benefits "low" across scenarios. For nursery areas, *V. Castelo* expects high provision across most pessimistic scenarios, while *Peniche*

[3] Upwelling intensity was used as an indicator of nutrient supply to coastal waters.

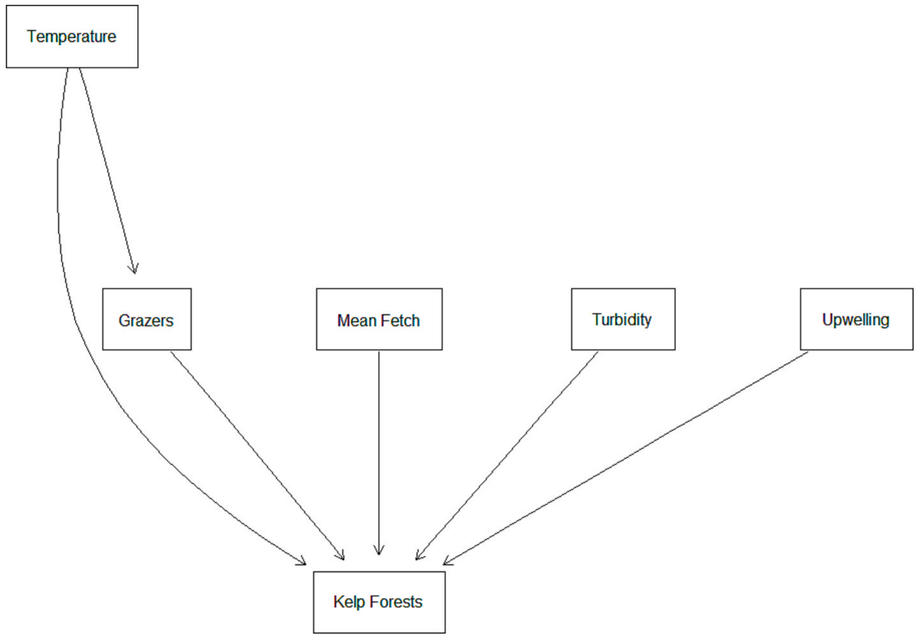

Fig. 2. Bayesian Belief Network (BBN) representing the factors influencing kelp forest condition in continental Portuguese coastal waters, based on measurement data. Kelp forests are directly influenced by environmental drivers such as temperature, mean fetch, turbidity, and upwelling, as well as indirectly influenced by temperature through its effect on a key biological driver: grazers. Temperature reflects annual mean sea surface temperature; grazers represent herbivore pressure; mean fetch captures long-term exposure to wind and waves; turbidity indicates light availability for photosynthesis; and upwelling reflects the intensity of wind-driven vertical nutrient transport. Arrows indicate hypothesized causal relationships.

expects lower provision. However, in *Peniche,* small variations occur between the different ES provision states in any scenario (up to 5 pp in variation). Considering carbon sequestration and water purification services, the provision in most scenarios is "high" for both locations, while aquaculture potential is already *"low"* in the current state, with this probability increasing under other scenarios.

Regarding *Sines*, experts anticipate that kelp forests will remain in *Poor* condition due to identified environmental and biological drivers, consistently predicting *"low"* provision levels for all associated ES (see Fig. A3 in the supplementary materials). As for the *Ria Formosa*, experts also indicated *Poor* conditions of seagrass meadows across scenarios. However, despite the *Poor* condition of seagrasses, experts highlighted positive outcomes for the provision of services (see Fig. A4 in the supplementary materials). Most ES have higher probabilities of *"high"* provision, except for emblematic species that only present *"low"* provision levels. Nonetheless, when considering the hypothetical scenarios, *"low"* provision outcomes become more likely. Still, for erosion control and water purification services, only small variations occur between the different provision states across all pessimistic scenarios (up to 13 pp in variation).

The developed BBNs also enabled us to assess how specific improvements in marine forest conditions could influence the services generated in these areas (see Figs. 4 and 5). If conservation or restoration actions were to be implemented, better outcomes for marine forests' condition could potentially be achieved. Restoration efforts in *V. Castelo* that improve kelp condition to *Good* could increase the probability of *"high"* service provision by up to 30 pp. Similarly, in *Peniche*, services such as biodiversity, nursery areas, carbon sequestration, and water purification could improve up to 40 pp for *"high"* provision. However, services related to aquaculture potential and health benefits are expected to remain *"low"* despite *Good* condition of kelp. In *Sines*, substantial changes could be observed if the kelp condition improved. Here, kelp's best possible outcome according to experts' opinions is achieving an *Average* condition. In such circumstances, services like biodiversity, nursery areas, carbon sequestration, and water purification would most likely deliver higher provision levels, with increases up to 40 pp. Aquaculture and health benefits would still present a low probability of high provision around the region. For seagrass meadows in *Ria Formosa*, improving its condition to *Good* would enhance biodiversity, carbon sequestration, erosion control, and water purification up to 30 pp, nursery areas by 40 pp, and emblematic species provision by 10 pp.

3.2. Bayesian Belief Network using measurement data

A clear result that emerges from the large set of models estimated is that the best-performing model is the one with the lowest number of factors. In other words, the most parsimonious model – specifically, the one where all variables have only two states – consistently performs better. Under the simulated datasets, this result holds, and no meaningful differences were found when using *MLE* or the *Bayes* algorithm as approximately 50 % of the simulations yielded lower prediction error with *Bayes* and 50 % using *MLE*. Given the very limited number of observations, it's clear that the performance driver is the dimensionality of the model rather than the choice of the algorithm itself. This issue is so severe that neither algorithm was able to estimate most of the CPTs in each model. This limitation seriously compromises the reliability of the inferences. The solution to this fact in the *bnlearn* package is to either accept missing probabilities or draw them from the uniform distribution. Furthermore, the trade-off between empirical and expert-based modelling approaches to formulate hybrid BBNs or the use of data augmentation could provide additional solutions.

The result obtained suggests that under severe data restrictions, not only are parsimonious models better at prediction, but it might be useful to consider alternative solutions to BBNs, such as expert-based data. To better understand what this means, we observe the results from two specifications. In the original dataset, without simulations, the best performing model was estimated using *MLE*, with 2-factor variables, our baseline specification: BN[222222_MLE]. Our second specification considers the structure of the BBN estimated using expert-based data. In this specification, we have the kelp individuals variable with 3 factors and the drivers with 2 factors, except for water temperature, which has 3 factors. We call this specification BN[322232_MLE]. This second

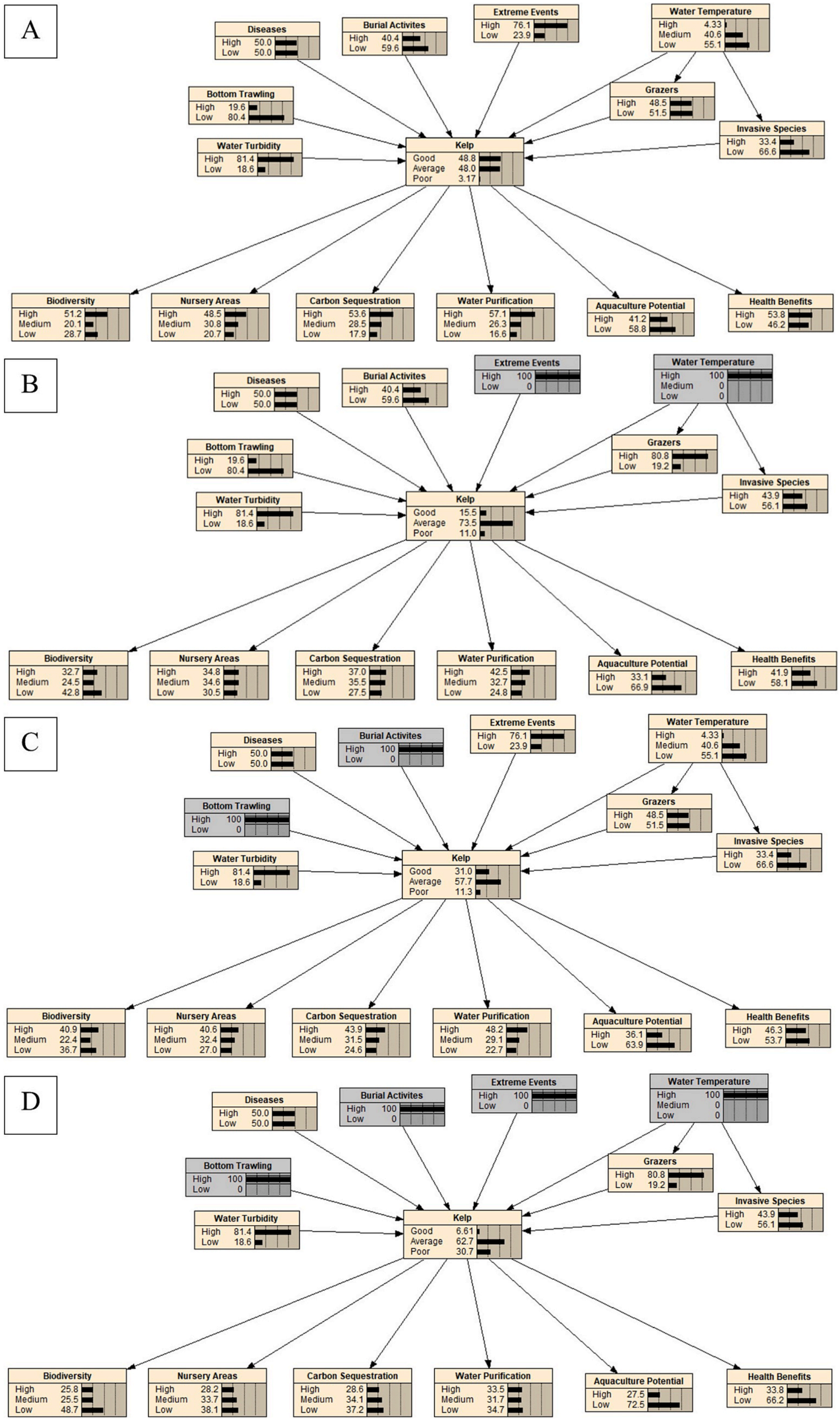

Fig. 3. Kelp forests condition to different scenarios for the Viana do Castelo region. In grey are all the drivers that were changed for scenario analysis purposes. A – Current state, B – Climate change scenario, C – Human pressures scenario, D – Cumulative impact scenario.

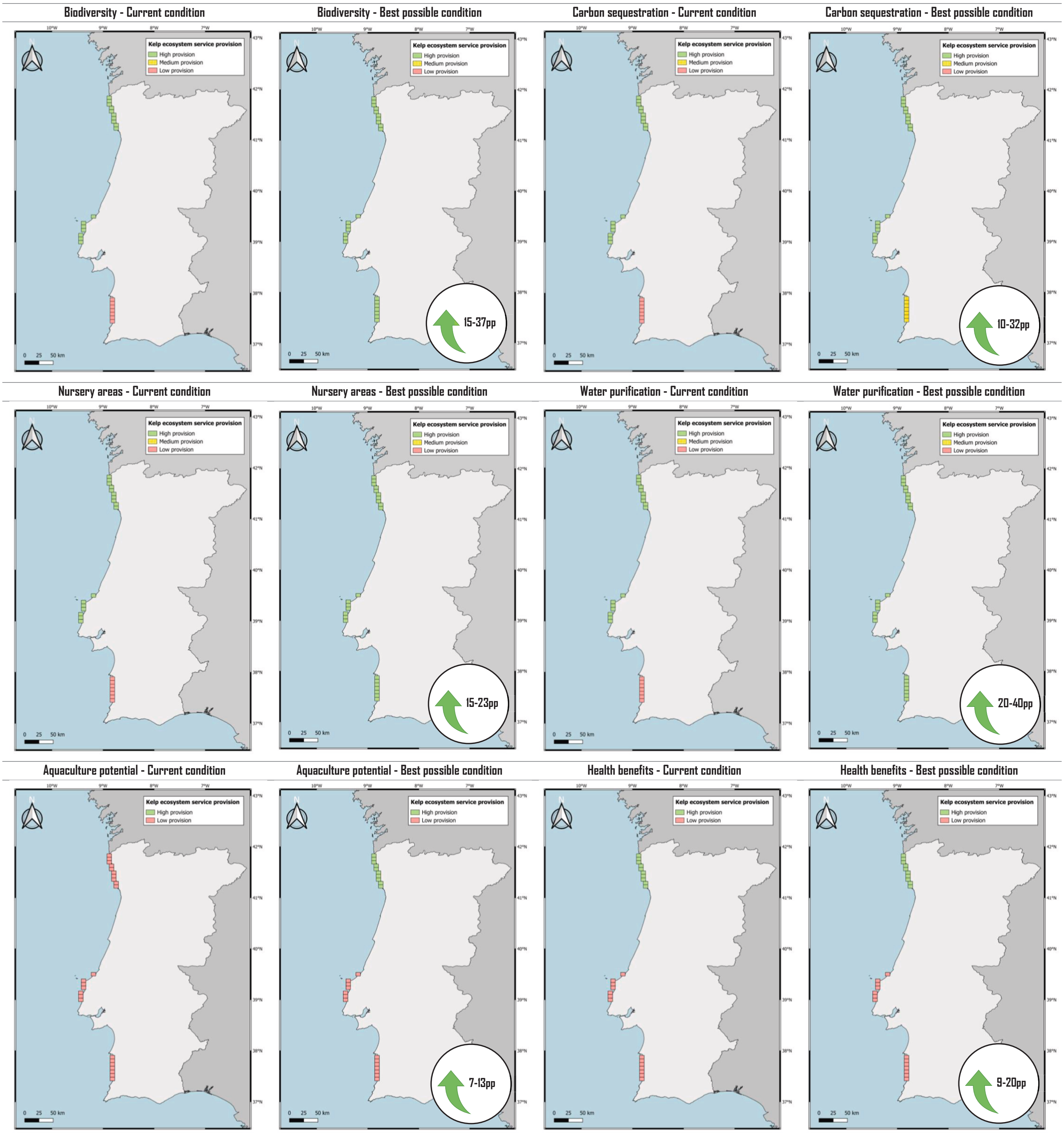

Fig. 4. Portuguese kelp forests ecosystem services provision. Information for each identified ecosystem service considering experts' belief of current and best condition outcomes (good in Viana do Castelo and Peniche, average in Sines). pp – percentage points. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

specification will be compared with the results from the expert-based BBN. While one could argue that we shouldn't compare BBNs with different dimensions, in our specification, not only are drivers independent between them, but also the conditional probabilities of the drivers given marine forests are also independent. This independence allows us to compare reduced and extended-form BBNs.

Comparing the Kelp expert-based BBN with the specification BN [322232_MLE], we observe significant differences in the probability of kelp provision given the state of the drivers. Considering the BN [322232_MLE] specification, with an average loss of 4.517415, it is clear that it was not possible to estimate all the CPTs, leaving in some cases blank values or draws from the uniform distribution. This limitation compromises the interpretation of the outputs, making downstream comparisons extremely challenging. Additionally, the estimated probability of *Poor* Kelp for specific scenarios (*e.g.,* the scenario of *"high"* turbidity and temperature, and *"low"* upwelling, irrespective of grazers'

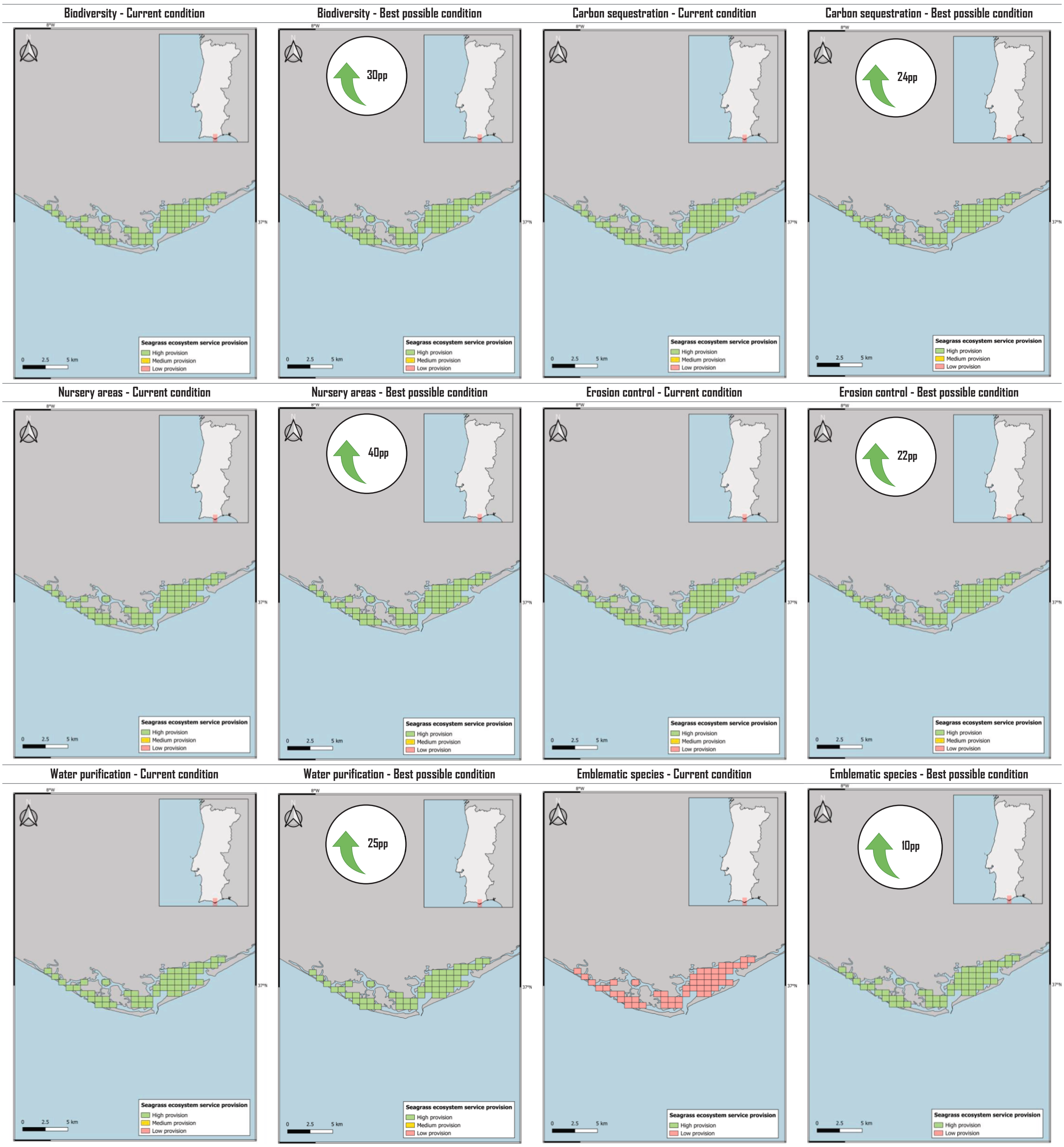

Fig. 5. Portuguese seagrass meadows ecosystem services provision. Information for each identified ecosystem service considering experts' beliefs on current and best condition outcomes (*i.e.,* good condition). pp – percentage points. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

estimations) was 100 %, in contrast to the expert-based BBN, as experts' outputs never presented a 100 % probability of any state of kelp. If we had opted for the best-performing model specification [222222_MLE], with an average loss of 3.932908, the same problems were observed with several CPTs drawing from the uniform distribution and several outputs showing a 100 % likelihood of *Poor* Kelp, contradicting the results from the expert-based survey. It's important to keep in mind that these results are likely driven by the choice of the interval. While factorizing the variables, we opted to use the quantile method rather than defining arbitrary intervals to avoid defining quantitative values to each driver as either "good", "average", or "poor" based on the feedback from the experts. This leads to a situation in which one of the factors has more probabilistic mass than the other, in particular when the drivers have a low number of factors, similarly, the lack of a reasonable number of observations does lead to the idea that there might be a contradiction between expert-based beliefs and the measured data. Unfortunately, without further measurements, it is not possible to conclude whether or not this divergence is due to a lack of data or to wrong priors from the experts. As we have obtained, CPTs from the BBNs estimated from field measurements not only contradict some of the results from the BBN using experts' data, but a substantial number of CPTs could not be estimated due to data limitations. This still holds in our robustness test. When we estimate a large number (819,200) of models using the simulated datasets, we still observe that the most parsimonious are preferred for prediction purposes. We also find that it is indifferent to choose between *MLE* or *Bayes,* as this is not what's driving the prediction error. In fact, over the 100 simulations, around half of them have lower average prediction error using *MLE* and the other half using *Bayes.* The immediate conclusion from this analysis is that under a limited data environment, we should either complement our analysis with or only use expert-based data.

4. Discussion

This study explores how different environmental conditions shape the functioning of kelp forests and seagrass meadows. It also addresses the practical difficulties of ecological modelling in data-limited contexts. By using BBNs, this study provides a structured framework that reveals distinct regional disparities in ecosystem health and highlight the threats posed by climate change and human activity, and underscores the need for targeted management actions.

4.1. Data dimensionality

The choice between an expert-based or data-driven approach in constructing CPTs reflects more than a debate about trusting expert knowledge versus adopting a data-centric approach. The methodology followed shows that the most important factor that drives the choice between expert-based data and field measurements is the availability, reliability, and size of observations from field measurements. When modelling complex networks with a high level of degrees of freedom, we require larger datasets that are impossible to obtain in circumstances such as those faced in this study. This is due to the lack of a large enough number of measurements, leading to a trade-off between *dimension* and *data*. This results in a trade-off between model complexity and data availability. It also constrains the methods we can use, especially when working with categorical data, which must be discretized. This discretization should not be defined *ad hoc,* nor should it rely on subjective classifications such as *Good*, *Average, or Poor,* without clear, operational definitions. Experts frequently emphasized that what constitutes a *Good* condition is location-specific – *e.g.,* what is considered *Good* at *V. Castelo* may differ from *Sines*. Therefore, even if the baseline and the factors that influence the condition at each site are similar, the natural environment is influenced by many different factors. As explained above, and to overcome the problem, in the datasets from field measurements, we followed an agnostic approach, partitioning the data based on their quantiles using the quantile discretization method. However, this partition is not innocuous as it allows to face larger dimensionality and, in consequence, finer detail, at the cost of requiring more data. On the other hand, we may estimate more parameters with less data if we choose a partition with smaller dimensionality. This issue was addressed by estimating a combination of models in which we partitioned our data between 2 and 5 factors. We opted for this number of factors as it not only allows to compare directly with a reduced version of the expert-based survey BBN, but it also provides a good degree of flexibility between a more parsimonious and a more complex BBN. For instance, for 5 variables, this required a total combination of 4,096 models.

This data-driven approach for discretization allowed us to deal with the issue of dimensionality by comparing models with a different number of estimated parameters per variable. Note that, without a large enough dataset, it is likely that the model will be unable to compute some of the conditional probabilities. To overcome this problem, conditional probabilities are drawn from the uniform distribution. While this might be a reasonable assumption for cases in which there are no extreme impacts to kelp and seagrass from the parent nodes, in real life we might witness situations in which increased values in temperature or fish herbivory might have an exponential impact on the provision of kelp and seagrass (Beca-Carretero et al., 2021; Franco et al., 2017; Rodríguez et al., 2022). In such cases, alternative distributions like the *Beta* distribution may be more appropriate, as they can be parametrized to model skewed or extreme probabilities reflecting ecological tipping points. However, this is beyond the scope of this work.

We estimated parameters using two algorithms for parameter learning: *Bayes* and *MLE.* In total, we estimated 8,192 models and then performed a 10-fold validation test to find the mean prediction error in each model. As expected, the best-performing model is the one relying on fewer number of factors per variable. This is particularly striking in both the best performing, BN[222222], and the parsimonious specification, BN[322232]. In both cases, it was not possible to estimate some of the CPTs. However, in the latter, some estimated CPTs contradict the results derived from expert-based knowledge. This result holds in simulated datasets, thus confirming our conclusion that in data-limited environments, the best approach to follow is an expert-based approach. Future steps can be performed by using a mixed approach where field measurements are supported by expert inputs (*e.g.,* integrated Bayesian priors or hybrid CPT construction), delivering integrated adaptable models that can reduce uncertainty and foster stakeholder engagement. However, this is also beyond the scope of this work, as we only compare data using the field measurements approach and the expert-based one.

4.2. Implications for conservation and restoration

BBNs are often characterized as valuable tools for addressing the uncertainty and complexity of natural systems, combining quantitative and qualitative data to showcase systems and their key elements (Marcot et al., 2006; Pham et al., 2021). Our expert-based BBNs, even in a data-limited environment, follow this premise and contribute to a better assessment of the intricate relationships within specific marine forests' locations along the Portuguese coast. By analysing our BBNs, we can understand how various nodes impact marine forests' provision and signal areas requiring further investigation.

Kelp forests exhibit variable conditions along the Portuguese coast. Studies by Tuya et al. (2012) and Pinho et al. (2015) show that kelp distribution is now confined to Northwestern Portugal. In contrast, *Peniche* and *Sines* – previously dominated by *Laminaria* species – have seen declines due to environmental and anthropogenic factors. Our results align with these findings, showing that the best probable outcomes are in the *V. Castelo* region, while *Peniche* and *Sines* are associated with lower kelp forest conditions. This is partially explained by the prevalence of identified drivers, particularly invasive and grazing species. Experts have raised concerns about the distributional ranges of invasive species and their potential impact on native kelp forests. Non-indigenous species like *Asparagopsis armata* are already present in Portuguese coastal areas, and studies are underway to assess their impact on native macroalgae (Franco et al., 2023; Silva et al., 2021). This could be even more alarming given the presence of important port facilities in these areas (*e.g., Sines* has the largest Portuguese port and one of Europe's fastest-growing ports), where ballast water discharges could potentially increase the prevalence of invasive species (Chainho et al., 2015; Fernando Alexandre et al., 2021). Additionally, herbivory significantly impacts kelp structure and survival (Barrientos et al., 2022; Franco et al., 2017). Climate change exacerbates these effects, with rising sea temperatures affecting kelp biology and influencing the distribution patterns of invasive and grazing species that compete with or prey on native kelp (Franco et al., 2015).

In this study, experts also identified concerns regarding existing human stressors. The *Ria Formosa* seagrass habitat is recognized for its ecological importance, providing nurseries for commercially important species and hosting emblematic seahorse species (Correia, 2022; Erzini et al., 2022; França et al., 2009). However, seagrass habitats are declining, and scientists are increasingly concerned about how environmental and anthropogenic drivers are influencing seagrass conditions (Cabaço and Santos, 2014; Cunha et al., 2013). Compound anthropogenic stressors – such as destructive and illegal fishing in seagrass meadows as well as coastal eutrophication and dredging in surrounding areas – are significant threats (Cabaço et al., 2010, 2008, 2005; Correia, 2022; Cunha et al., 2013, 2005). Moreover, the feeding habits of fish species *Sarpa salpa*, and the effects of climate change, especially through the migration of new invasive species, increase the pressure in the area (Goldenberg and Erzini, 2014; Martínez-Crego et al., 2021; Parreira et al., 2021). These stressors may lead to system potential tipping point dynamics, which can be more effectively explored using BBN modelling. Our data indicate that if these drivers persist, seagrass current *Poor* condition could increase by nearly 50 pp (Cumulative scenario, Fig. 4A in the supplementary materials). This is even more alarming given the importance of the *Ria Formosa* seagrass area to the region, where despite the current seagrass condition, experts still believe in the provision of significant ES levels (Current state, Fig. A4 in the supplementary materials). This decoupling between condition and ES provision should be further explored, and our data may support future assessments of ecosystem resilience in the region.

Furthermore, experts highlight the need for adaptation and mitigation mechanisms to address cumulative pressures on marine forests' habitats. Future conservation and restoration efforts should assess the real impact of these drivers, particularly in areas already experiencing decline (Cunha et al., 2013; Pinho et al., 2015). Expert-based BBNs can play a crucial role in this process by showing how marine forests' condition affects ES provision and guiding conservation actions to achieve sustainability. In this study, we recognize the cumulative impact of various drivers on marine forest habitats and identify which ES are most at risk if those pressures keep affecting kelp and seagrass conditions. Concerns about kelp forests revolve around biodiversity, nursery areas, carbon sequestration, and water purification provision. As for the provision of health benefits and aquaculture, based on the BBN outputs (low probability), experts consider that these services have low expression in Portuguese Kelp. *V. Castelo* is the only area where these values are not so striking. This could be attributed to the abundance of kelp forests in the area and the increasing demand for kelp-related products, that could promote future aquaculture projects (Cardoso et al., 2014; Ferreira et al., 2021; Pacheco et al., 2021; Pinho et al., 2015). Additionally, the region has a strong cultural heritage as kelp was historically used as soil fertilizer and in disease treatments (Cardoso et al., 2014; Gaspar et al., 2019). Although these practices are less common nowadays, they still influence kelp public perceptions. Regarding seagrass meadows, concerns are more evenly distributed across various services, but there is a notable recognition that the emblematic seahorse species is facing increasing challenges under current conditions. This is supported by current data showing the severe decline in seahorse abundance in the *Ria Formosa* over the years (Correia, 2022). Given their flagship value or the potential role as an indicator species, seahorses can help inform conservation prioritization within these vulnerable habitats.

Despite these pressures, our analysis indicates that if, by implementing restoration initiatives, marine forest conditions achieve the best possible outcomes for each area (*Good* condition in *V. Castelo*, *Peniche*, and *Ria Formosa*; *Average* condition in *Sines*), ES provision levels could increase by up to 40 pp (see Figs. 4 and 5).

4.3. Policy Implications

This study represents an important first step towards understanding the potential of reforestation actions in marine forest habitats along the Portuguese coast. Experts have raised significant concerns about the impacts of climate change on the structure and functionality of these habitats. Our BBN reveals that climate change, particularly rising sea temperatures, is affecting the condition of native kelp species (Climate change scenario Fig. 3, and Fig. A2 and A3 in supplementary materials). As previously mentioned, this warming trend is reshaping the distributional patterns of kelp species and exacerbating pressures from invasive and grazing species. These dynamics pose a challenge to kelp survival, particularly in regions like *Sines* and *Peniche*, where our models show the most substantial declines in kelp health. Also, *Sines* is characterized by intense port activity, which can further intensify marine forest declines. In *Ria Formosa*, similar pressures combined with destructive and illegal human activities are threatening one of Portugal's most popular natural habitats. This cumulative and synergistic set of stressors demands urgent attention, as it jeopardizes not only these ecosystems but also the sustainability of Portuguese marine forests. Without adequately targeting monitoring and mitigation, even healthier areas, such as *V. Castelo*, could face severe ecological challenges and potential regime shifts in the near future (Carnell and Keough, 2020; Sardanyés et al., 2024; Wilman, 2021). Addressing these challenges requires a strategic, data-informed scientific approach capable of delivering meaningful and long-lasting outcomes. To this extent, increased investment in marine data collection is vital to enhancing the accuracy and robustness of ecological models. This study supports this need by examining the performance of ecological models under data-limited conditions. Further, complementing empirical modelling approaches with expert evidence, such as our expert-based BBNs, can provide tailored information to support conservation efforts not just to coastal Portugal, but across diverse marine regions. Our findings contribute to the broader goal of enhancing ecological resilience and promote adaptive management mechanisms by demonstrating how both data and expert inputs can improve decision-making in complex and uncertain environments.

Europe's mission to restore its oceans and waters by 2030 (European Commission, 2024), underscores the urgency of such actions. This mission seeks to protect and restore marine and freshwater habitats, contributing to "relevant upcoming marine nature restoration targets, including degraded seabed habitats and coastal ecosystems". Hence, prioritizing reforestation actions in critical habitats like marine forests is essential, given their ecological and socio-economic value to human society (Eger et al., 2022; Morris et al., 2020; Tan et al., 2020). Our BBNs indicate that restoration initiatives would not only improve the condition and provisioning of marine forests but also contribute to mitigating climate change impacts and fostering community resilience. Nonetheless, reforestation efforts must be strategically targeted to maximize effectiveness. Attempting restoration in severely degraded areas, such as *Sines*, may yield limited success due to irreversible ecological shifts driven by the combination of rising sea temperatures with intense human activity. Instead, restoration should focus on regions where interventions are more likely to mitigate and adapt to environmental and anthropogenic pressures. Based on our findings, we recommend prioritizing *V. Castelo*, *Peniche,* and *Ria Formosa*. These areas hold the greatest potential for ecological recovery and socio-economic benefits. For instance, *Ria Formosa* seagrass meadows are vital not only for ecological health but also for local fisheries, coastal protection, and the cultural fabric of surrounding communities. By focusing on regions with the highest potential for success, this research provides a foundation for aligning national efforts with Europe's broader environmental agenda.

4.4. Limitations and future Directions

Qualitative assessments can reflect local knowledge and are essential to address ecosystem provision trends (Busch et al., 2012). Yet, we recognize the limitations of this approach, including potential research bias and subjectivity, as well as significant time required for expert selection and data analysis.

Our study faces the challenge of representing a highly complex and dynamic natural system, involving numerous drivers. Such representations inevitably simplify the real-world context, where there is a trade-off between ecological realism and the potential usability of the model (Marcot et al., 2006). Also, complexity and poor measurability are inherent to ES provision processes (Landuyt et al., 2013). Larger, more complex models would be more difficult to understand, more challenging to incorporate experts' responses, and would also bring additional uncertainty. Future studies should aim at reducing subjectivity by incorporating empirical observations. However, this will require extensive data often unavailable for specific locations (*e.g.,* coastal Portugal, Sines). For example, our BBNs included 15 nodes, requiring both experts' inputs and field measurements – often insufficient. Conversely, opting for a simpler model would have omitted key ecological drivers, compromising ecosystem representativeness.

Given such limitations, we adopted what we considered the most balanced compromise between ecological relevance and data availability. Despite these limitations, the BBNs were deemed a realistic representation of marine forest provision by experts. If future studies provide additional data, it could be incorporated into the framework, enhancing provision assessment robustness in those areas. Previous studies have used BBNs to assess marine forests' provision, usually focusing on a limited number of drivers (*e.g.,* Wu et al., 2015, 2018). Our study offers a more comprehensive perspective and maps significant areas of marine forests' provision. Although we do not consider more granular ES provision data (*i.e.,* variation in ES provision within our study areas), we were able to assess regional variations of marine forests ES provision between study areas. This information can be valuable to future studies by comparing experts' beliefs with empirical evidence and by offering inputs for ES valuation studies. Ultimately, this study can also support more sustainable local public policy decision-making (van Dam et al., 2013; Yuniarti et al., 2021), better informing stakeholders about system responses to various pressures and prioritizing areas for restoration.

5. Conclusions

This study explores the potential of marine forests to provide ES based on their ecological condition while addressing the challenges of applying complex ecological modelling in data-limited contexts. Despite the inherent limitations of qualitative assessments and simplified representations of natural systems, our findings demonstrate the value of BBNs as realistic, integrative tools for evaluating the cumulative impact of environmental and biological drivers on kelp and seagrass habitats.

The results reveal significant regional variability in the condition of Portuguese marine forests and highlight growing concerns related to climate change, grazing pressure and invasive species. Our BBN approach underscores the importance of targeted, spatially informed conservation and restoration actions, and offers a flexible framework to support evidence-based decision-making at local and regional scales.

Crucially, while recent field efforts have expanded our understanding of marine forest ecosystems, data gaps remain. Continued investment in marine ecological monitoring is essential to enable the integration of data-driven approaches that can produce more robust and scalable policy recommendations. We do hope this work contributes to advancing that goal, supporting biodiversity conservation, climate resilience, and the sustainable use of coastal ecosystems.

CRediT authorship contribution statement

Miguel Fernandes: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **João Seixo:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **João N. Franco:** Writing – review & editing, Resources, Data curation. **Maria A. Cunha-e-Sá:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2025.101789.

Data availability

The code that can be used to replicate the results of this paper is available through the following link (https://github.com/Fingarfan/BlueForests). Note that the dataset used in this code is not available. It can be made available upon request. If you have any questions relative to the code, please email the authors.

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