Vol. 441: 197–212, 2011
doi: 10.3354/meps09354

MARINE ECOLOGY PROGRESS SERIES
Mar Ecol Prog Ser

Published November 15

Integrated modelling tools to support risk-based decision-making in marine spatial management

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ABSTRACT: The implementation of an ecosystem approach to marine spatial management requires practical tools to support risk-based decision-making. We combined a Bayesian Belief Network with a Geographical Information System (GIS) for the spatially explicit quantification of the ecological and economic risks of spatial management options. As an example we assessed the German exclusive economic zone (EEZ) in the North Sea to determine the potential effects of 2 scenarios on the vulnerability of plaice *Pleuronectes platessa* to fishing, fishing fleets and their revenues. In the first scenario we simulated a shift in plaice distribution due to changes in bottom temperatures to assess spatial management options. Then we imitated an expansion of offshore wind energy development with an associated reallocation of international fishing effort to assess the ecological and economic consequences. We predicted that an increase of 0.5°C in the average bottom temperature would require a significant reduction in fishing effort to maintain the current relative level of the vulnerability of plaice to fishing. The likely consequences of the second scenario were a homogenous increase in plaice catches around the areas closed for fishing, together with a decrease in the vulnerability of plaice to fishing within 17% of the study area. Our results showed the great potential of this framework to integrate the spatially explicit assessment of the economic and ecological risks of spatial management options. We conclude that this modelling framework can support the implementation of an ecosystem approach to marine spatial management, as it enables the derivation of probabilistic estimates which can be used directly in risk-based decision-making.

KEY WORDS: Bayesian Belief Network · Fishing effort · GIS · Plaice · *Pleuronectes platessa* · Offshore wind energy · Regression kriging

INTRODUCTION

Worldwide, the intensity and frequency of marine uses is increasing, together with their demand for sea space, which results in growing human pressures on coastal and marine ecosystems (Halpern et al. 2008). Thus, there is an urgent need for integrated and ecosystem-based management approaches that enable a sustainable development of marine resources while safeguarding marine environmental health (Leslie & McLeod 2007, Ruckelshaus et al. 2008). Place-based or spatial management such as marine spatial planning (MSP) is seen to facilitate an ecosystem-based management (Lackey 1998). MSP is an integrated planning framework that informs management about the spatial distribution of activities in the ocean in order to support current and future uses of ocean ecosystems and maintain the delivery of valuable ecosystem services for future generations in a way that meets ecological, economic and social objectives (Foley et al. 2010). National and international policies and directives such as the EC Marine Strategy Framework Directive (MSFD; Commission E 2008) recognise this need to address human pres-

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sures in the marine environment and promote an ecosystem approach to management by using tools such as MSP. For instance, the national implementation of the MSFD comprises an assessment of human pressures and their impacts on the marine environment, together with the specification of programs of measures, such as management and mitigation measures or monitoring programs. Thus, future management measures are inevitably linked to the spatial management of human uses as it is defined in national marine plans. Spatial management tools such as MSP and ocean zoning are being developed and implemented worldwide (Douvere & Ehler 2009). Based on growing international experience, practical guidelines for spatial planning already exist (COM 2008, Ehler & Douvere 2009). However, these general guidelines do not provide the scientific means to evaluate the economic and environmental consequences of spatial management options. Thus, a number of authors have already addressed the lack of integrated tools to assess the economic and environmental risks of spatial management options (Foley et al. 2010, Tallis et al. 2010, Olsen et al. 2011).

In general, spatial management options can result in 2 types of conflicts, namely conflicts between human activities and the environment and conflicts between different human activities. The former type of conflict requires an assessment of the risks of anthropogenic activities, which vary in their intensities and footprints on ecosystem components that are sensitive to those activities. An increasing number of studies has presented practical approaches for quantifying the impacts of specific human activities or the cumulative impacts of a number of activities on ecosystem components (Halpern et al. 2008, Ban et al. 2010, Foden et al. 2010, Stelzenmüller et al. 2010b). In the context of marine planning, the impact of one human activity on other activities is being studied to a lesser extent. One example is a study by Berkenhagen et al. (2010) in which the cumulative economic impacts for the fisheries sector were analysed in relation to the development of offshore wind energy in the German exclusive economic zone (EEZ). As yet, studies assessing the risks of spatial management options by integrating more than one sector of human activity and by analysing their potential impacts on each other and on ecosystem components are lacking.

Current approaches in land use management for defining and assessing spatial management options encompass, for instance, multi-criteria analyses (MCA) or spatial optimization techniques, such as Pareto optimality (see Kennedy et al. 2008, Polasky et al. 2008 and references therein). While the former approach requires a weighting of management objectives, the latter eliminates the need for the prior specification of weights. Thus, in the marine environment, an increasing number of case studies are concerned with spatial optimization problems, for instance, in relation to the design of networks of marine protected areas (Smith et al. 2008, Martin et al. 2009). GIS-based tools, such as Marxan (Watts et al. 2009) or Ecopath (Christensen et al. 2009), are used to find optimal locations based on defined constraints and targets. While those tools can support the development of spatial management options, an evaluation of the risks and consequences of those management options are beyond their capability. However, a spatially explicit assessment of the risks of possible spatial management scenarios and related uncertainies is crucial for the spatial and temporal allocation of human activities, as is regulated in MSP. Thus, the classical method of testing hypotheses provides, in general, a poor basis for environmental management decision-making as it lacks the ability to predict the consequences of those hypotheses (Ellison 1996).

Bayesian Belief Networks (BNs) are models that graphically and probabilistically represent correlative and causal relationships among variables and can account for uncertainty (McCann et al. 2006). BNs have been successfully applied to natural resource management to address environmental management problems and to assess the impact of alternative management measures (Varis et al. 1990, Marcot et al. 2001, Nyberg et al. 2006). A recent study by Stelzenmüller et al. (2010a) combined GIS analysis and BNs to support marine planning tasks by assessing 'what if' scenarios for different planning objectives and related management interventions. Following this methodological concept, we developed, in the present paper, an integrated modelling framework to assess the potential consequences of spatial management options in the German EEZ of the North Sea and in adjacent coastal waters. Moreover, the present study aims to test the framework's ability to combine the assessment of the ecological and economic risks of spatial management options in relation to 2 scenarios at the resolution of fishing fleets. Such a characterisation and quantification of risk is a crucial step in an ecological risk assessment framework, which, in general, comprises problem formulation, hazard identification, risk analysis and risk characterisation (Hayes & Landis 2004, Landis 2004).

The MSP for the German EEZ is legally binding and contains designated preference areas for a number of sectors, except fishing, together with special areas of conservation (Natura2000 sites) (BMVBS

2009). The plan specifies a number of high level objectives, such as the promotion of offshore wind energy use (installed capacity of 20 000 MW by 2030) or the protection of natural resources by avoiding disruptions to and pollution of the marine environment. However, the likely spatial expansion of offshore wind energy development is beyond the boundaries of designated preference areas. Further individual wind farm licenses will be subjected to environmental impact assessments, and fisheries management options are currently being assessed for Natura2000 sites (Pedersen et al. 2010). In spite of the implemented marine spatial plan, this uncertain development of offshore renewables generates a number of future spatial management scenarios with different economic consequences for the sectors involved (Fock 2011b).

Thus, for the study area, we developed an integrated modelling framework combining BNs and GIS to assess the risks of possible spatial management options in relation to 2 scenarios for international fishing fleets, the vulnerability of plaice *Pleuronectes platessa* to fishing and the revenues generated within the study area. Those scenarios describe: (1) a shift of resource distribution due to environmental change and the assessment of spatial management options under a defined management objective, and (2) the spatial expansion of wind energy development with a related fishing effort allocation and the prediction of ecological and economical risks. Finally, we tested the capability of this approach to support a risk assessment framework in the context of marine spatial management under different baseline conditions and management objectives.

MATERIALS AND METHODS

BN development

Our study area comprised the German EEZ of the North Sea with its adjacent coastal waters (Fig. 1). In a

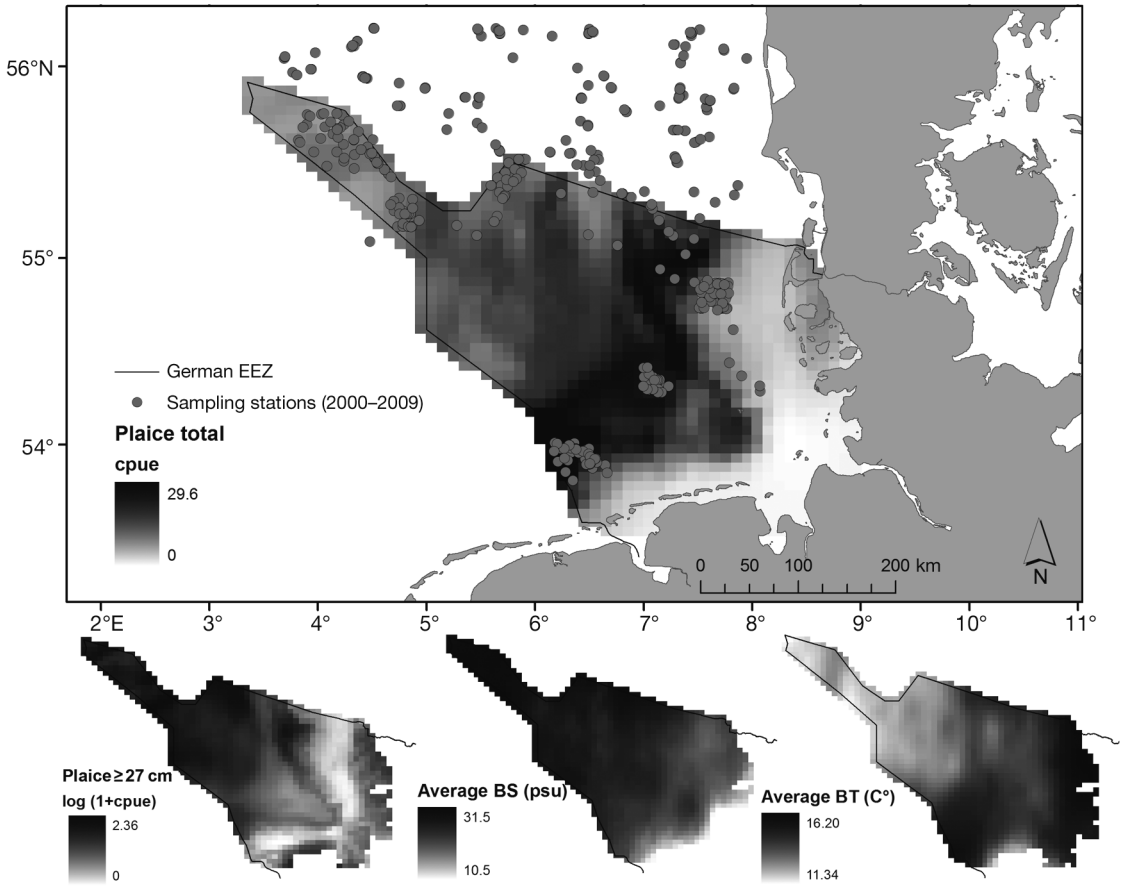

Fig. 1. Study area with 7 m beam trawl sampling stations, estimated spatial distribution patterns of catch per unit effort (cpue) of total plaice (upper panel), plaice *Pleuronectes platessa* ≥27 cm (lower, left panel), average (2000–2009) bottom salinity (psu) (lower, middle panel) and temperature (C°) (lower, right panel). EEZ: exclusive economic zone; BS: bottom salinity; BT: bottom temperature

GIS we superimposed a 3 by 3 nautical mile (n mile) vector grid for the subsequent analysis. The grid size was determined by the maximum resolution of fishing effort data (see Fock 2008). This grid contained all the attribute information necessary to populate the conditional probability tables (CPTs) of the model nodes (Fig. 2). The model nodes and associated data are described in more detail below (see Table 1).

Average bottom temperature and average bottom salinity

Bottom temperature and bottom salinity are environmental predictor variables for plaice *Pleuronectes platessa*. From the ICES oceanographic database (www.ices.dk/ocean/aspx/HydChem/HydChem.aspx) we extracted sea bottom temperature and salinity data for the years from 2000 to 2009 for the third quarter of each year. Within the study area we interpolated the annual temperature and salinity values on a high-resolution grid (0.6 n mile or 0.01 decimal degrees), using ordinary kriging (Cressie 1991). We summarised the values on the 3 n mile vector grid to represent average bottom temperature and salinity.

Depth

The average depth is an environmental predictor variable for plaice. For each grid cell we derived the average depth (m) from the General Bathymetric Chart of the Oceans (GEBCO) digital atlas (www.gebco.net).

Sediment

We obtained sediment data from the Federal Maritime and Hydrographic Agency and assigned each cell to a sediment type (www.bsh.de). In total, we allocated 17 sediment categories to the grid cells which were comprised of 4 main sediment categories (mud, M; fine sand, fS; medium sand, mS; and coarse sand, cS) with different sorting categories ranging from very poorly (vps), poorly (ps), moderately (ms), well (ws) and very well (vws).

PlaiceTotal and Plaice≥27 cm

For the study area, we extracted plaice catch data from the third quarters of annual beam trawl surveys from 2000 to 2009 (393 tows) using a 7 m beam trawl with a towing time of 30 min with the German research vessels 'SOLEA I' and 'SOLEA II' (see Fig. 1). We also extracted, for each sampling station, the bottom temperature and bottom salinity records. With the help of a length–weight relationship (w [kg] = a length^b; a = 0.0069 and b = 3.1084; vTI data), we computed catch per unit effort (cpue; kg per 30 min) for total plaice catches (referred to as total) and for the size class ≥27 cm (referred to as ≥27 cm), as 27 cm corresponds to the minimum landing size of plaice. To account for the inter-annual variability (p = 0.05) in plaice catch data (total and ≥27 cm), we standardised cpue data with the help of generalized linear models (GLM) using the factor 'year' as a predictor variable. As described in Stelzenmüller et al. (2007), we derived calibration coefficients by back-transforming

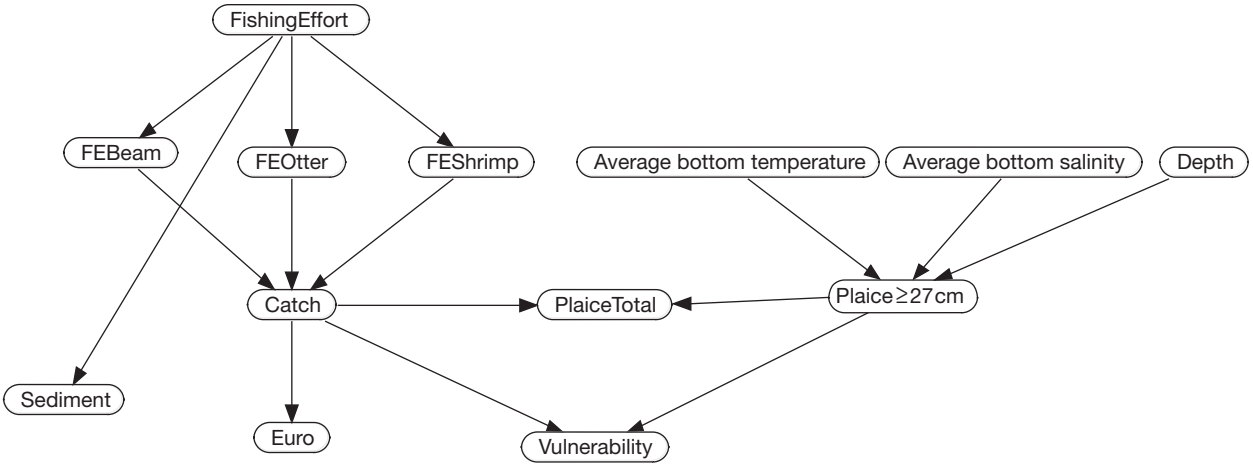

Fig. 2. Conceptual model showing the key variables used to predict the overall level of vulnerability of plaice *Pleuronectes platessa* to fishing as a function of the total catch and catch per unit effort (cpue) of plaice ≥27 cm. Abbreviations defined in Table 1

Table 1. Overview of model nodes, description of data collection and states. All model nodes reflect attributes from the 3 by 3 n mile vector grid. cpue: catch per unit effort

Node	Description	States
FishingEffort	Sum of total hours fished per 3 n mile grid cell in 2008 by German, Dutch and Danish beam and otter trawlers potentially catching plaice *Pleuronectes platessa* ≥27 cm	0–33; 33–100; 100–200; 200–700; 700–3400
FEBeam	Total hours fished per 3 n mile grid cell in 2008 by German, Dutch and Danish beam trawlers	0–0.4; 0.4–6; 6–30; 30–110; 110–1330
FEOtter	Total hours fished per 3 n mile grid cell in 2008 by German, Dutch and Danish otter trawlers with a mesh size ≥80 mm	0; 0–1.9; 1.9–5; 5–17; 17–575
FEShrimp	Total hours fished per 3 n mile grid cell in 2008 by German, Dutch and Danish beam trawlers fishing for brown shrimp with a mesh size 16–31 mm	0; 0–1.3; 1.3–3.9; 3.9–16; 16–414
Catch	Total German, Dutch and Danish landings (kg) of plaice ≥27 cm in 2008 per 3 n mile grid cell derived from logbook data	0–40; 40–500; 500–2500; 2500–7000; 7000–44000
Euro	Total catch of plaice ≥27 cm multiplied by the average market price per kg in 2008 (1.89 €)	0–80; 80–1100; 1100–5000; 5000–13000; 13000–90000
Sediment	Sediment data obtained from the Bundesamt für Seeschifffahrt und Hydrographie (Federal Maritime and Hydrographic Agency, www.bsh.de) with 17 sediment categories: mud (M), fine sand (fS), medium sand (mS) and coarse sand (cS) with different sorting categories ranging from very poorly (vps), poorly (ps), moderately (ms), well (ws) and very well (vws) sorted	Sms, cSvws, cSws, fSms, fSps, fSvps, fSvws, fSws, Mms, Mps, mSms, mSvps, mSvws, mSws, Mvps, Mvws, Mws
Average bottom temperature	Annual bottom temperature (C°) distributions (www.ices.dk) were estimated with ordinary kriging (Cressie 1991) and averaged from 2000 to 2009 for each 3 n mile grid cell	11.3–12.7; 12.7–13.7; 13.7–14.3; 14.3–15; 15–16.3
Average bottom salinity	Annual bottom salinity (psu) distributions (www.ices.dk) were estimated with ordinary kriging (Cressie 1991) and averaged from 2000 to 2009 for each 3 n mile grid cell in every grid	10.5–24.2; 24.2–26.2; 26.2–28; 28–29.2; 29.2–31.5
Plaice≥27cm	Log(cpue + 1) of plaice ≥27 cm per 3 n mile grid cell predicted with regression kriging (Hengl et al. 2007) using aggregated and standardised 7 m beam trawl catch data (2000–2009, third quarter of each year)	0–0.6; 0.6–0.9; 0.9–1.4; 1.4–1.8; 1.8–2.4
PlaiceTotal	Cpue of plaice per 3 n mile grid cell predicted with regression kriging (Hengl et al. 2007) using aggregated and standardised 7 m beam trawl catch data (2000–2009, third quarter of each year)	0–4; 4–8; 8–11; 11–15; 15–30
Vulnerability	A relative measure of the vulnerability of plaice ≥27 cm to beam and otter trawling within the study area defined as: $\frac{\text{cpue}_i}{\sum_{i=1}^{n}\text{cpue}} \Big/ \frac{\text{Total catch}_i}{\sum_{i=1}^{n}\text{Total catch}}$ with the first term reflecting the modelled relative proportion of plaice ≥27 cm (log 1 + cpue) within a grid cell (i) and the second term showing the relative proportion of the total catch within a grid cell	0 (State 0, no); >10.12 (State 1, very low); 3.45–10.12 (State 2, low); 1.67–3.45 (State 3, medium); 0.38–1.67 (State 4, high); <0.38 (State 5, very high)
Depth	The average depth (m) for each grid cell was derived from the General Bathymetric Chart of the Oceans (GEBCO) digital atlas (www.gebco.net)	12–26; 26–36; 36–40.4; 40.4–44; 44–72

the parameter estimates (Quinn II & Deriso 1999) and transformed cpue data by dividing the raw cpue by the appropriate power coefficient (exponential function of GLM parameter estimate). We predicted the average (2000 to 2009) spatial distribution pattern of plaice with standardised and aggregated cpue data with the help of regression kriging, a hybrid technique which combines regression techniques with kriging of the regression residuals (see details of the method in Hengl et al. 2007). Recent studies used this modelling technique to estimate the spatial distribution pattern of commercial species such as plaice, sole *Solea solea* and thornback ray *Raja clavata* (Maxwell et al. 2009) or patterns of fishing effort density around marine protected areas (Stelzenmüller et al. 2008). This spatial modelling technique requires a number of analysis steps. First, we assessed the relationships between the cpue data of plaice (total and ≥27 cm) and the environmental variables at the sampling locations using generalized additive models (GAMs)

(Hastie & Tibshirani 1986). We assessed possible colinearity with the help of Pearson product moment correlation between the cpue data and the environmental variables (average bottom temperature, average bottom salinity and depth) and among the environmental variables. For the GAM calculations, we allowed for possible non-linear effects of the environmental variables using natural splines (Venables & Dichmont 2004) while controlling the risk of overfitting by limiting the degrees of freedom. From the full set of calculated GAMs, we selected the best models by the lowest value of the Akaike information criterion (Akaike 1973) and predicted the cpue of total plaice and plaice ≥27 cm log(1 + cpue) for each grid cell of a high-resolution grid (0.6 n mile) (referred to as trend maps). We corrected the spatial GAM estimates by conducting a geostatistical analysis of the GAM residuals, which is the second step in the regression kriging process. We described the spatial structuring of the GAM residuals using semivariograms and fitted the parameters of spherical models (nugget effect, sill and range) with a weighted least-squares fitting procedure (Cressie 1991). Afterwards, we predicted a value of the residuals using ordinary point kriging for each 0.6 n mile grid cell (referred to as autocorrelation map). We then combined the respective trend and autocorrelation maps to produce continuous maps of the average distribution of plaice. In a final step, we transferred the predicted cpue of plaice (total and ≥27 cm) to our standard analysis grid (3 n mile) within the GIS.

FishingEffort, FEBeam, FEOtter and FEShrimp

We combined German, Dutch and Danish VMS (vessel monitoring system) and logbook data from 2008 to calculate fishing effort and total catch (marketable catch) within in each 3 n mile grid cell. Logbook data are not defined on these fine levels, but it is a proportional calculation to effort (see below). Original VMS data consist of the vessel identification number, position, speed and heading. We assessed the fishing effort for métiers (fleets) which catch plaice ≥27 cm as target species and bycatch; these comprised beam trawls fishing for brown shrimp with a mesh size of from 16 to 31 mm (referred to as FEShrimp), beam trawls with a mesh size of from 80 to 99 mm targeting flatfish (referred to as FEBeam) and demersal otter board fishing for flatfish with a mesh size of from 80 to 99 mm (referred to as FEOtter). We also aggregated the total fishing effort of those fleets (referred to as FishingEffort). We categorised the VMS data into signals indicating 'fishing' and 'not fishing' with the help of the individual vessel speed. The position of each vessel was then allocated to the 3 n mile grid cells (i.e. 100 fine rectangles per ICES rectangle), and the time interval between 2 positions was summed up to the amount of fishing effort spent per grid cell (hours fishing). Since the time interval between each position can be up to 2 h, there is a considerable amount of 'unseen' activity by each vessel. We took this uncertainty into account following the method developed by Fock (2008), whereby each registration was substituted with a discrete set of positions with a high probability of vessel presence.

Catch and Euro

We derived the total catch from plaice landings indicated in the logbook data. We aggregated landings according the international VMS data and calculated the total catch (kg) for 2008. The total catch was distributed proportionally to the effort to each 3 n mile grid cell and multiplied by the mean price (1.89 €) of plaice of German landings in 2008 to calculate the revenue (referred to as Euro) gained per grid cell.

Vulnerability

To reflect the pressure of the fishing activities on the plaice population, we constructed a measure of vulnerability which reflects, at a given location, the relative local pressure of fishing on the resource in relation to its estimated spatial distribution. Thus, we defined the vulnerability (V) of plaice ≥27 cm to fishing as:

$$V_i = \frac{\text{cpue}_i}{\sum_{i=1}^{n} \text{cpue}} \Big/ \frac{\text{Total catch}_i}{\sum_{i=1}^{n} \text{Total catch'}} \qquad (1)$$

with the first term reflecting the ratio of cpue on plaice ≥27 cm (log 1 + cpue) within a single grid cell i and the cpue cumulated over all cells. These cpue data refer to surveys and therefore better represent the abundance. The second term indicates the same ratio for commercial catches. The lower the coefficient is, the higher the vulnerability for plaice ≥27 cm. We then categorised the vulnerability values to 6 vulnerability states using quartiles: State 0 = no; State 1 (>10.18) = very low; State 2 (3.45 to 10.18) = low; State 3 (1.67 to 3.45) = intermediate; State 4 (0.38 to 1.67) = high; State 5 (0.04 to 0.4) = very high.

Our vulnerability index V_i reflects the overlap of population and catches, but it can also be interpreted

in terms of fishing mortality:

$$V_i = \frac{\text{cpue}_i + \sum_{i=1}^{n} \text{Total catch}}{\sum_{i=1}^{n} \text{cpue} \times \text{Total catch}_i} \quad (2)$$

as:

$$V_i = p_{\text{plaice},i} \times F_{\text{plaice}} \times \frac{1}{f_i} \quad (3)$$

with $p_{\text{plaice},i}$ being the occurrence of plaice within a cell, F_{plaice} as the fishing mortality for the entire stock and f_i as the local fishing mortality (Rijnsdorp et al. 2006).

We used the Netica software system (www.norsys.com) (see details in Spiegelhalter & Dawid 1993 on the inference algorithm implemented in Netica) to develop the BN model and combined the in- and output files with the GIS vector grid. The BN model (Fig. 2) represents the vulnerability of plaice ≥27 cm to fishing and the revenues generated from plaice catches within the study area as a function of fishing effort and the average distribution pattern of the resource, which is, in turn, influenced by the environmental variables bottom temperature, bottom salinity and depth. Fishing effort and the environmental variables are parent nodes and are considered to be independent of each other. Each parent node has different discrete states (e.g. temperature or depth categories) with an associated probability of occurrence. The FEBeam, FEOtter and FEShrimp, reflecting the fishing effort (hours fished) of the different métiers, are child nodes of the fishing effort node. Further, the vulnerability node is defined as a child node of the total catch node and the resource node (plaice ≥27 cm). The revenue node is a child node of the total catch node. The child node total plaice is influenced by the total catch node and the plaice ≥27 cm node, while the sediment node showing the sediment categories affected by fishing is a child node of the fishing effort node.

One of the advantages of using BNs is that empirical data, as well as expert opinion, can be used to define the prior probabilities. For the present study, however, we built the prior probabilities for each node in our model based on GIS data and not on expert opinion. Thus, the model reflects the current level of 'evidence' for relationships, and the data were used to populate the conditional probability tables (CPTs).

BN sensitivity and performance assessment

We conducted a sensitivity analysis and assessed the overall performance of the BN. First, we evaluated the sensitivity of the vulnerability node to the influence of the parent nodes by calculating the variance reduction (Marcot et al. 2006). Next, we tested the performance of the model by removing the observations for the vulnerability node and a subsequent calculation of the maximum-likelihood state. This allowed us to estimate the Type I error rate (%) by comparing the predicted beliefs of the unobserved vulnerability node with the true values for the vulnerability node and to evaluate the classification success rate using the spherical payoff index (see detailed description in Marcot et al. 2006):

$$\text{MOAC} \frac{P_c}{\sqrt{\sum_{j=1}^{n} P_j^2}} \quad (4)$$

where MOAC is the mean probability value of a given state averaged over all cases and ranges from values of 0 to 1 (1 being the best model performance), P_C is the probability predicted for the correct state, P_j is the probability predicted for state j and n is the number of states.

Marine management scenarios

With the help of the BN-GIS framework we explored possible management options under a defined management objective in case of environmental change and assessed potential consequences of a spatial management scenario for the fishing fleets, the vulnerability of the plaice population and the revenues in the area of interest. Thus, after building and testing the BN as described above, we used it to infer the behaviour and response of the variables to different scenarios. We defined 2 marine management scenarios which included the setting of objectives and predicted the consequences of those objectives. We defined the current state as the baseline or 'do-nothing' scenario.

Scenario 1

What management targets for fisheries are required to maintain the current vulnerability of plaice in the case of environmental change? We defined the maintenance of the current average vulnerability of plaice to fishing as the management objective. We simulated an increase in the relative average bottom temperature in our study area of 0.5°C with now 10% of the area being in State 1, 12% in State 2, 13.7% in State 3, 31.4% in State 4 and 32.9% in State 5. We then predicted the responses of the variables and

the potential consequences for the vulnerability of plaice. Afterwards we used the BN model to predict a possible management intervention for the total fishing effort to maintain the current average measure of vulnerability of marketable plaice.

Scenario 2

How does the vulnerability of marketable plaice change after the development of offshore wind energy and a related displacement of fishing effort? One of the high level German management objectives for the EEZ of the North Sea is an installed capacity of offshore wind energy of 20 000 MW by 2030. We used the current application areas for wind energy development (provided by the Bundesamt für Seeschifffahrt und Hydrographie [BSH]; www.bsh.de) and reallocated the current fishing effort with the help of a set of simplified displacement rules (see Fig. 3). Although fishermen's behaviour is likely much more complex, we reset the fishing effort for grid cells within the wind energy application areas to zero and redistributed the same amount of fishing effort. In the GIS we constructed 3 buffer rings (3, 10 and 15 km) around the application areas and redistributed the fishing effort of each fleet with 70% of the respective effort to the 3 km buffer area, 20% to the 10 km buffer area and 10% to the 15 km buffer area. Further cells where no fishing activity occurred in 2008 were excluded from the redistribution of activities. This displacement scenario should account for the fact that fishermen tend to fish very close to closed areas such as marine protected areas or fishing closures (e.g. Murawski et al. 2005, Stelzenmüller et al. 2008).

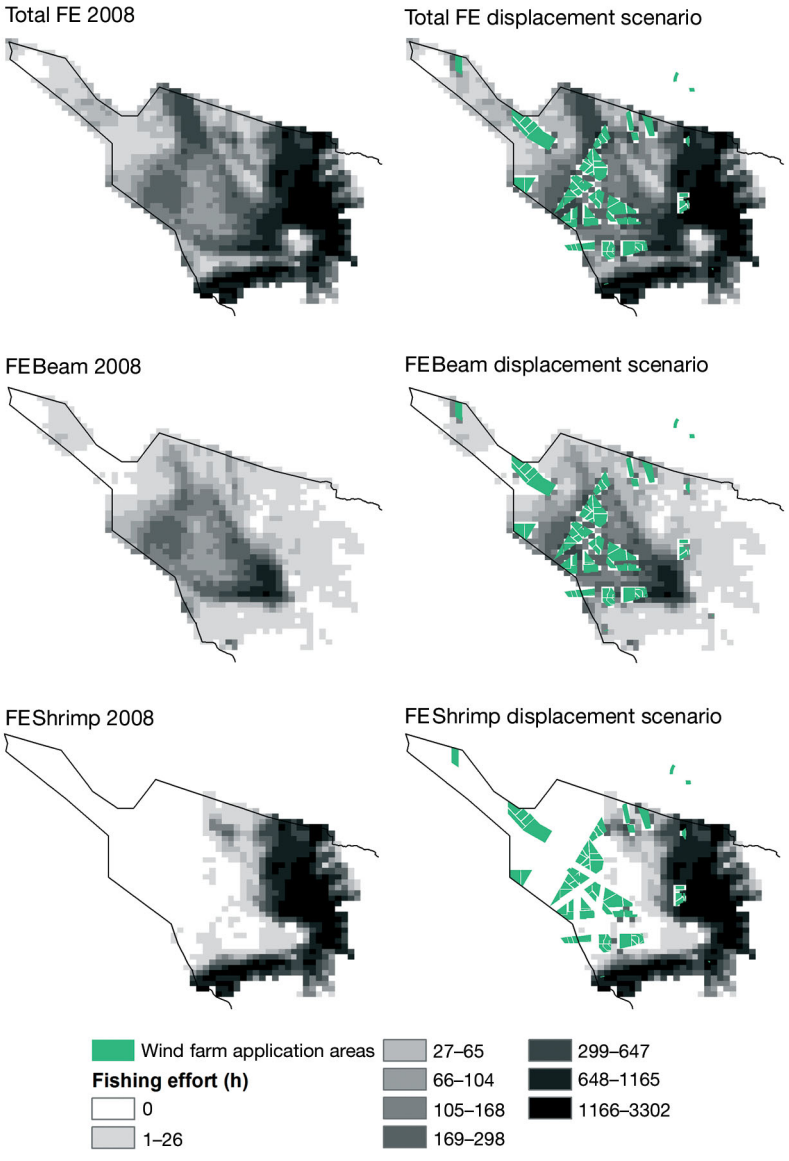

Fig. 3. Spatial distribution patterns of the total international fishing effort (FE) in 2008 of the beam trawl fleet (FEBeam) and shrimper fleet (FEShrimp) (left panels) and respective fishing effort displace-ment scenarios (right panels)

RESULTS

Baseline scenario

The complete derived model describing the relationships between fishing effort, total catch of plaice, environmental parameters and the distribution of the resource is presented in Fig. 4. For each node representing a continuous variable a weighed mean (the mean value weighted by the probability of occurrence) and a Gaussian standard deviation is shown. Thus, we computed an expected mean of 546 h fished in total by international fishing fleets. Also 20.2% of the surface area has been fished from 0 to 33 h in total by international fishing fleets. The baseline scenario also revealed that there is a 19.4% chance of catching from 0 to 40 kg of plaice ≥27 cm within any given grid cell. The revenue node (Euro) showed that there is a

22.2% chance that any given gird cell would generate between 80 and 1100 € from German plaice landings in 2008. The expected revenue was 12 100 € with a standard deviation of 21 000 €. A further 42.8% of the fishing activities took place on very well sorted fine sand (fSvws) and 26.5% took place on well sorted fine sand (fSws). Under current fisheries management and the predicted spatial distribution of the resource, we computed a likelihood of 8.4% that a grid cell experienced a vulnerability of 0 (State 0) and a 26.4% chance of being in the vulnerability State 4 (high).

BN sensitivity and performance assessment

Table 2 shows the results of the sensitivity assessment of the BN model as the computed variance reduction for the vulnerability node. The total catch of plaice had the greatest influence followed by the revenue of plaice. The revenues ranked high due to the significant correlation with the catch values. Interestingly, the fishing effort of the beam trawlers reduced the variance by 9.4%, while the total fishing effort reduced the latter by only 3.92%. The environmental variables were the least influential ones. The calculation of the Type I error rate revealed a slightly increased value of 25.6% for the vulnerability node. However, the classification success rate (spherical payoff), which ranges from 0 to 1, with 1 being best model performance, indicated a relatively accurate model for predicting vulnerability with a value of 0.8. The confusion matrix provided in Table 3 indicates the accuracy of the beliefs of the vulnerability node predicted by the BN model using the data described in Table 1.

Scenario 1

The consequences of the simulated increase in weighted average bottom temperature from 13.9 to 14.4°C are displayed in Fig. 5a. Under this environ-

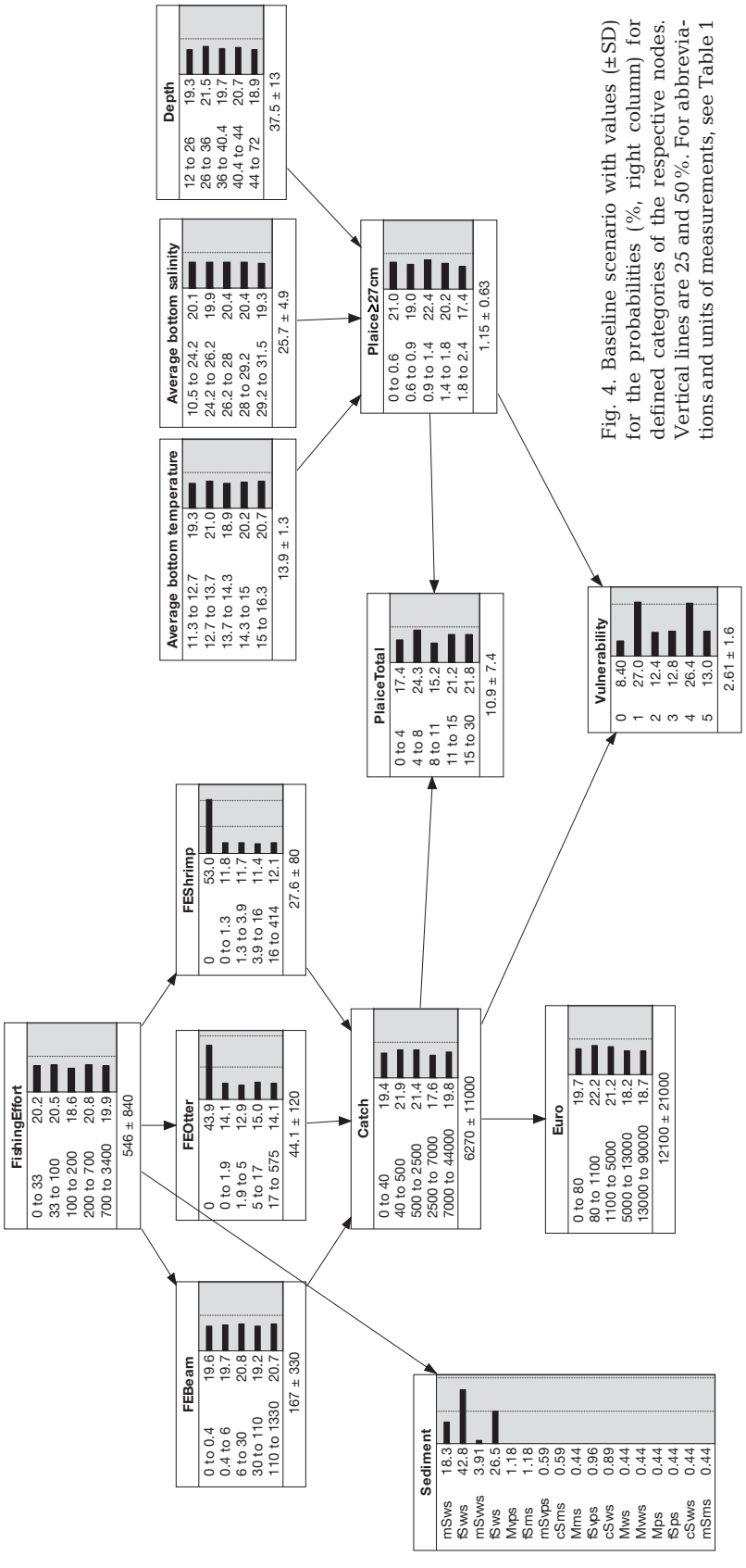

Fig. 4. Baseline scenario with values (±SD) for the probabilities (%, right column) for defined categories of the respective nodes. Vertical lines are 25 and 50%. For abbreviations and units of measurements, see Table 1

Table 2. The variance reduction reflects the sensitivity of the vulnerability node to the findings of the parent nodes. For abbreviations, see Table 1

Node	Variance reduction (%)
Catch	57.50
Euro	54.10
PlaiceTotal	14.20
FEBeam	9.43
FishingEffort	3.92
Plaice≥27cm	2.39
FEOtter	2.06
FEShrimp	0.84
Sediment	0.18
Average bottom temperature	0.17
Average bottom salinity	0.17
Depth	0.07

mental change scenario the weighted average vulnerability for plaice increased slightly from 2.61 to 2.64 caused by a marginal decrease in surface area (or number of cells) in the vulnerability States 0, 2, 3 and 4 and a concurrent increase in surface area in States 1 and 5. This increase in the average vulnerability is not significant as it is still within the confidence limit of the standard deviation. However, under the management objective of maintaining the current expected value of vulnerability, one possible management intervention would be to increase the surface area (or number of cells) in fishing effort State 1 by 20% and State 2 by 16%, together with a reduction of the surface area in fishing effort State 3 by 8% and States 4 and 5 by approximately 14% (see Fig. 5b). This possible intervention reflects a reduction of the weighted average international total annual hours fished per grid cell (equals 30 km^2) by 60% (from 546 to 197 h), with the FEBeam being affected most (from 167 to 87 h). The consequences for revenues would be a possible decrease in the expected mean catch by 840 to 5430 kg, with an associated decrease in mean revenue per grid cell area of 1500 € (given constant prices).

Table 3. Confusion matrix showing the accuracy of the beliefs of the vulnerability node predicted by the Bayesian Belief Network (BN) model using the data described in Table 1

Actual vulnerability state	State 0	State 1	State 2	State 3	State 4	State 5
0	22	31	0	0	0	0
1	4	279	28	0	0	0
2	0	7	177	2	0	0
3	0	1	110	13	61	0
4	0	0	19	9	345	2
5	0	0	4	0	41	91

Scenario 2

The BN model predicted the beliefs for all states of the total catch and vulnerability nodes based on the defined fishing effort reallocation after the closure of the wind farm application areas to fishing (Fig. 6). The predicted distribution of the catches showed a rather homogenous increase of catches around the areas closed for fishing. The arithmetic mean of catches under Scenario 2 is approximately 3000 kg higher than under the baseline scenario. The predicted pattern of the most probable vulnerability states showed a decrease in the surface area in the vulnerability State 5 and an increase in the surface area in States 2 and 4. A closer examination of the spatial distribution patterns of predicted vulnerability states showed, for instance, for State 2 a general increase in the number of cells in the north-eastern part of the study area under Scenario 2 (Fig. 7). In Fig. 8 the surface area per vulnerability state is compared between the baseline scenario and Scenario 2. Thus, the predicted consequences or costs of Scenario 2 were that 12% of the surface area would experience an impairment of vulnerability. In contrast, the benefit would be that approximately 17% of the surface area would experience a lower level of vulnerability compared to the baseline scenario and 71% of the surface area would not experience any change.

DISCUSSION

We assessed the risks of possible spatial management options for the vulnerability of plaice *Pleuronectes platessa* to fishing and the fisheries' economic viability in the German EEZ of the North Sea and its adjacent coastal waters in relation to 2 scenarios. In the context of a risk assessment framework the spatial predictions of plaice cpue, fishing effort, total catch and revenue, and plaice vulnerability correspond to the risk analysis step, where the likelihood of the exposure to a hazard and its likely effects are described.

Our spatial models of plaice cpue represent only average estimates of the plaice distribution in the third quarter of each year between 2000 and 2009, and the data on fishing effort are only from 2008; thus, the results are limited to a relative interpretation. However, they suffice for

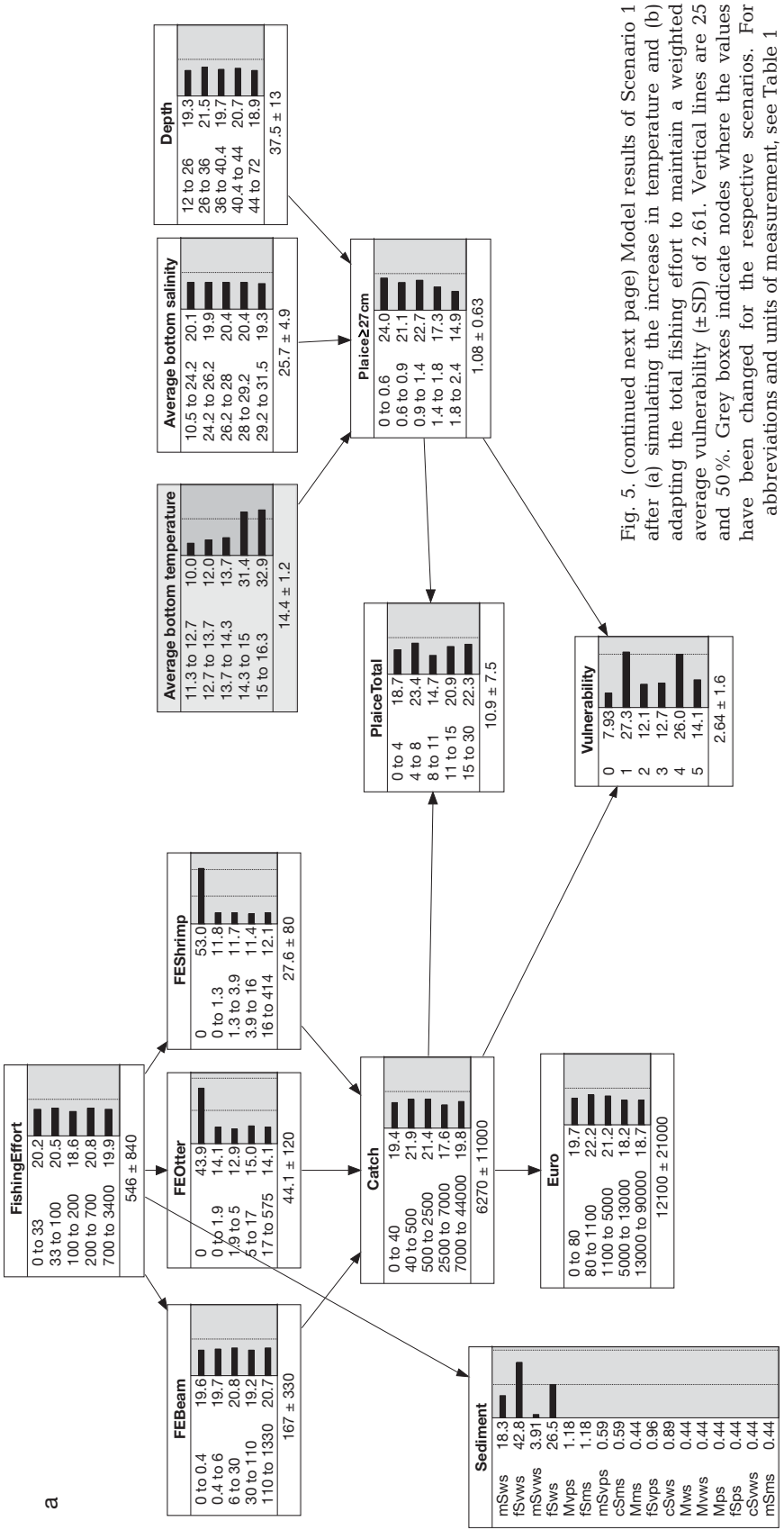

Fig. 5. (continued next page) Model results of Scenario 1 after (a) simulating the increase in temperature and (b) adapting the total fishing effort to maintain a weighted average vulnerability (±SD) of 2.61. Vertical lines are 25 and 50%. Grey boxes indicate nodes where the values have been changed for the respective scenarios. For abbreviations and units of measurement, see Table 1

constructing a measure of the relative vulnerability of plaice to fishing as an indicator of the sensitivity of an ecosystem component to human pressures. Here, we followed the general concept of vulnerability reflecting the ratio between an effect indicator and an exposure indicator (see a detailed review by De Lange et al. 2010 of the methods to assess sensitivity and vulnerability). Recent studies by Fock (2011a) and Fock et al. (2011) showed that such a measure of vulnerability (i.e. the risk of an ecosystem component) can also be expressed as a relative measure accounting for the negative and positive effects of disturbance such as fishing.

Our presented measure of vulnerability does not reflect the condition of the plaice population and its general vulnerability to fishing, instead it reflects a static measure built on the ratio of 2 proportions. As already indicated, our proposed spatial V_i can also be interpreted in relation to fishery mortality, allowing for a more general assessment of vulnerability of fish populations to fishing. Thus, the vulnerability index V_i may be applied in cases where full ecological risk analysis cannot be parameterised. It may also be applied to stocks for which analytical assessments are not available.

We presented 2 different scenarios to test the capability of our approach to assess the consequences of spatial management options and to resolve those risks spatially. In other words, such an assessment corresponds to the risk characterisation step of a risk assessment framework. The first scenario simulated an increase in the average bottom temperature of 0.5°C and showed one possible management option under the management objective of maintaining the expected average vulnerability. Although this scenario reflects a rather hypothetical set up, the results highlighted the importance of specifying the management regulations of fishing activities

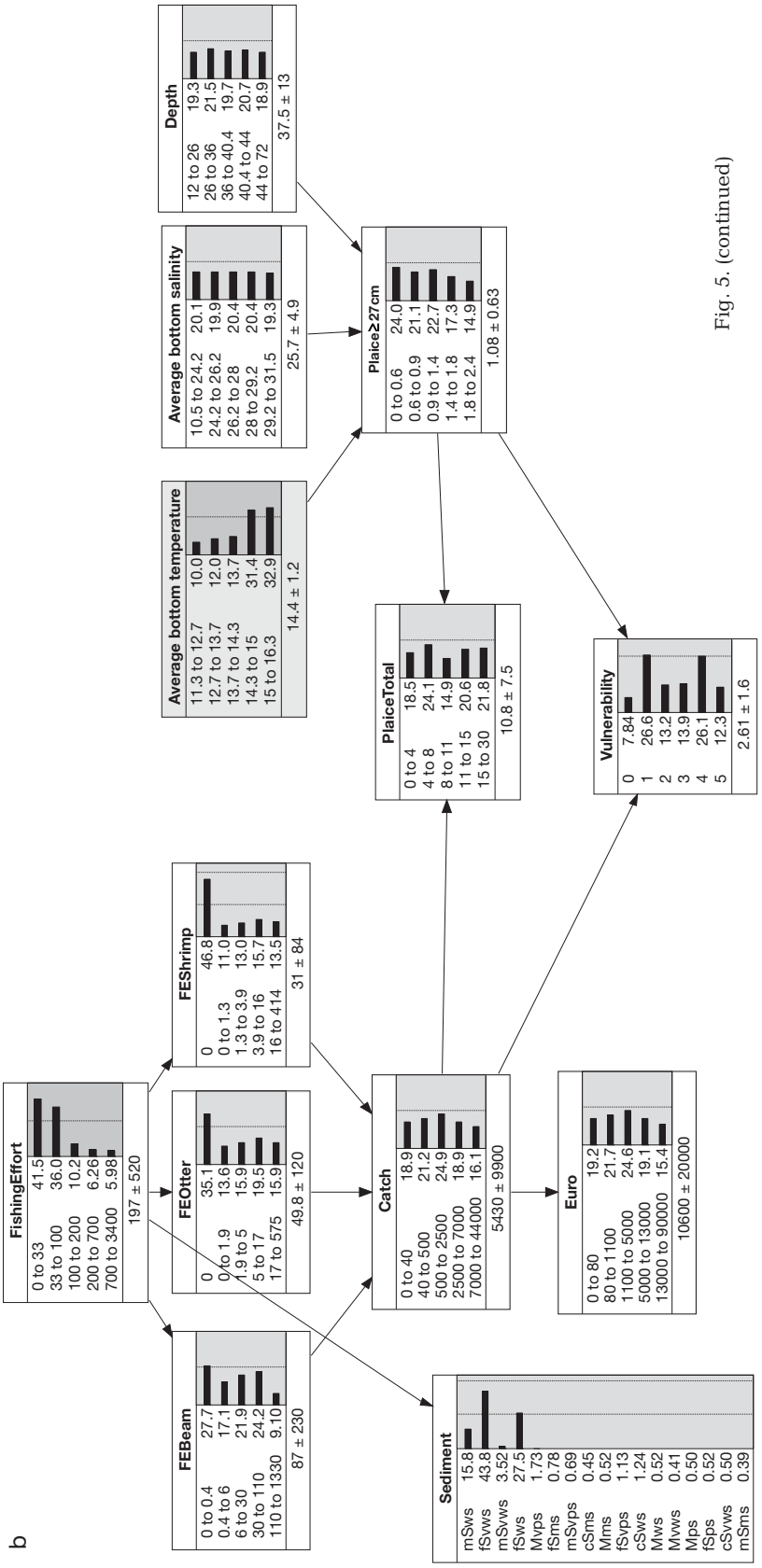

Fig. 5. (continued)

on the level of fishing fleets. In our example, the beam trawl fleet was affected most by the overall restriction of the annual hours fished. In addition, different fishing activities have different impacts on the environment, which is, in turn, the result of the catchability of the gear used and its bottom contact (Fock et al. 2011). The scenario results also revealed changes in the relative magnitude of pressure on the different sediment categories due to changes in fishing effort. Hence, future applications of the BN model could also explore scenarios of potential management measures to achieve multiple management objectives, such as the reduction of pressure on certain sediment categories (which may reflect certain benthos communities) and the prevention of a certain state of plaice vulnerability. In addition to a spatial shift in plaice distribution, other expected impacts of such an environmental change scenario may be seen in a shift in fishing seasons due to possible changes in the spawning behaviour of plaice (Munk et al. 2009). Although the effects of increasing temperatures since 1989 on the quality of plaice nursery grounds are not clear, possible impacts may comprise a mismatch of benthic production and energy requirements of 0-group flatfish (Teal et al. 2008). Thus, the international fleet targeting plaice in the study area would need to adapt to such changes. Leaving aside any potential implication on fishing costs, the economic consequences of changes in seasonality will most likely influence supply and demand dynamics and therefore prices and revenues. Thus, this scenario could be used further to explore the effects of management options on the level of fishing fleets and to identify adaptation options when pressures are added that cannot be managed, such as climate change.

Our second scenario was explicitly designed to test the framework's capability for supporting the decision-making process in marine spatial manage-

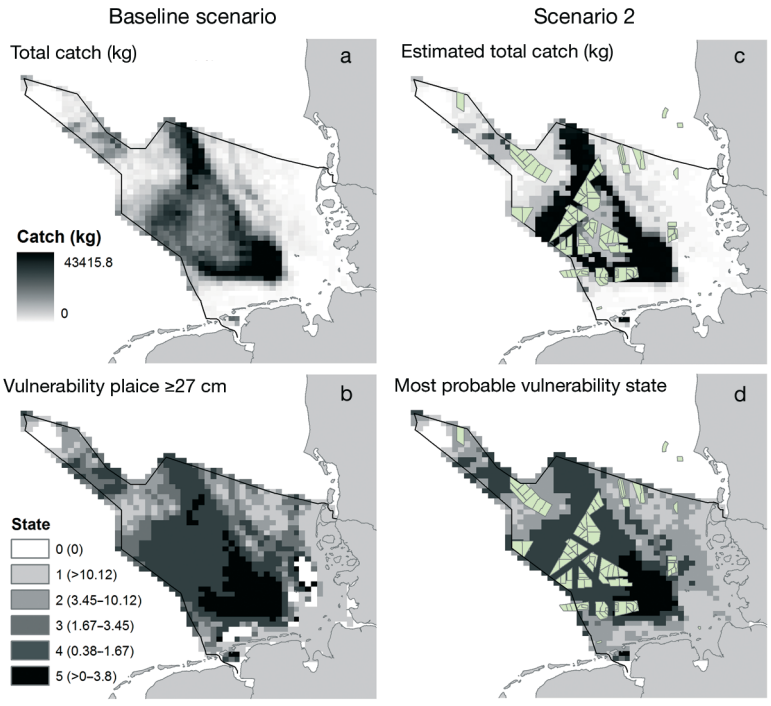

Fig. 6. (a) Total catch (kg) derived from vessel monitoring system and logbook data in 2008, (b) current vulnerability of plaice ≥27 cm to fishing pressure, (c) the predicted distribution of total catch and (d) the most probable vulnerability state of plaice ≥27 cm after the displacement of fishing effort (Scenario 2) due to implementation of offshore wind farms (green in c,d)

ment. We used the current application areas for offshore wind farms as a basis for reallocating the international fishing effort which occurred in those areas in 2008. A recent study by Berkenhagen et al. (2010) estimated that the flatfish fishing grounds impacted by the wind farm scenario previously provided about 50% of flatfish catches in the German North Sea. This shows the importance of accounting for preference areas in fishing in the development of spatial management options. For this scenario our set of fishing effort reallocation rules aimed to represent a linear decrease in fishing effort with increasing distance from areas closed to fishing (see Stelzenmüller et al. 2008 and references therein). Yet fishermen's responses to areas closed to fishing are often more complex and call for case-specific models, like the bio-economic model for Mediterranean swordfish by Tserpes et al. (2009) or individual-based models which incorporate factors such as fuel prices or market development (BEMMFISH 2005). The aggregation of fishing vessels in smaller areas outside closed areas could also lead to increased competition and conflict (Shipp 2003). Moreover, the social consequences of fishing effort allocations due to spatial management measures could also comprise a general interest of fishermen to increase fishing capacity due to increased steaming time, which stands in contrast to current fisheries management practice (Agardy 2010, Agardy et al. 2011 and references therein). For the North Sea only a few studies analyse the resource distribution, spatial management, effort allocation and economic aspects of fisheries separately or in pairs (Marchal et al. 2002, 2007, Poos et al. 2009). As yet, studies integrating all aspects are still lacking. This highlights the fact that the prediction of fishermen's responses to management often represents a knowledge gap that hinders the construction of more realistic scenarios which are crucial for sound decision-making in ecosystem-based management.

Once improved knowledge on fishing patterns and fishermen's responses becomes available, such information could be incorporated into our modelling framework; this would enable the integration of other relevant factors and their relationships or other model outcomes representing, for instance, the spatial distribution patterns of fishing activities. Future applications could also address the potential cross-border consequences (economic and ecological) of spatial management scenarios in the German EEZ of the North Sea.

Both scenario outcomes reflect spatial management options under assumed management objectives rather than final solutions. Like any modelling technique our BN-GIS framework, constructed to describe complex relationships between human activities and sensitive ecosystem components, is constrained by the available data at the relevant spatial scale. Thus, interpretations of the results are specific to the spatial scale of the study area (see Marcot et al. 2006). Further, BN models require the full probability structure of the variables and their relationships, which is not a straightforward task in cases with poor data or which require expert judgement. Also, there are limitations regarding the level of complexity that can be consistently assessed by BN models (Marcot et al. 2006).

Any decision-making process in environmental management requires both the assessment of probabilities of certain outcomes (risk analysis) and the consideration of a manager's attitude to risk (risk management) in order to validate the level of uncertainty about whether or not a management decision

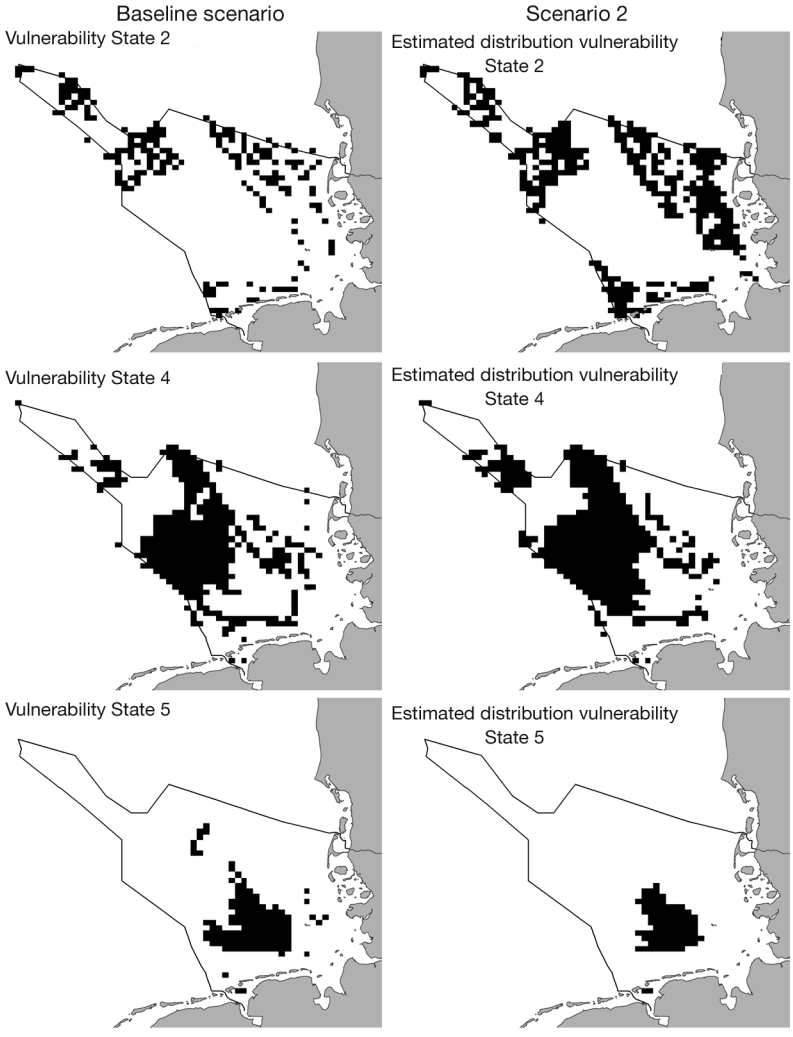

Fig. 7. Example results for Scenario 2 on the assessment of changes in spatial patterns of vulnerability states (black squares) after the closure of wind farm application areas to fishing, together with a displacement of fishing effort. Distribution of cells in the vulnerability States 2, 4 and 5 according to the baseline scenario (left panels) and the distribution patterns of the predicted States 2, 4 and 5 in Scenario 2 (right panels) are displayed

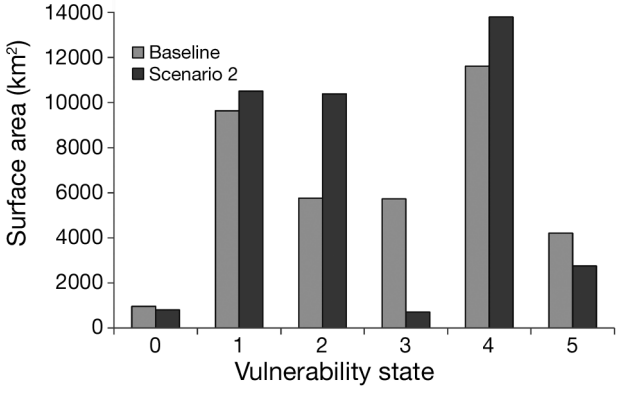

Fig. 8. Relative comparison of surface area (km^2) and vulnerability state between the baseline scenario and Scenario 2

will lead to the desired outcome (see Marcot et al. 2006 and references therein). BNs can incorporate nodes representing potential management decisions or the utility of outcomes and allow for a comparison of outcome values weighted by their relative probabilities. Ultimately, to be of direct use for decision-making in marine spatial management, BN models and related scenarios require clear management objectives. Marine spatial planning aims to achieve multiple objectives by managing human activities in space and time; thus, assessing the risk of failing to complete those objectives is an essential component of adaptive management (Douvere & Ehler 2009, 2010).

In summary, our results showed the potential range of applications of the spatially explicit and integrated modelling framework. One of the main advantages of this approach is the ability to spatially examine the spatial pattern of uncertainty related to spatial management options, which is crucial for MSP. Further, to support the actual decision-making process in spatial management, the modelling framework presented needs to be adapted to each case according to the available data, spatial scale and management objectives. For instance, once the driving factors of fishermen's behaviour are known, more realistic scenarios can be defined to assess spatial management options in our study area. Ideally, management objectives also include a definition of targets and thresholds against which predicted changes can be assessed. In other words, to adopt our proposed vulnerability measure in a risk-management framework, thresholds would be required reflecting the maximum level of acceptable vulnerability of plaice to fishing. We conclude that the approach presented would be a useful tool in facilitating informed decisions through the spatially explicit assessment of potential risks and in relinquishing the related uncertainty concerning spatial management options.

Acknowledgements. The effort data used in the present study for Denmark and the Netherlands were collated during the plaice evaluation project (PBOX funded by DG Mare) and were kindly provided by Josefine Egekvist (DTU Aqua) and Doug Beare (IMARES).

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Editorial responsibility: Jake Rice, Ottawa, Canada

Submitted: May 19, 2011; Accepted: August 19, 2011
Proofs received from author(s): November 10, 2011