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An integrated modelling approach to support an ecosystem based management of multiple uses in the German EEZ of the North Sea

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Marine spatial planning in the German EEZ of the North Sea was previously driven by offshore wind farm development and the designation of conservation areas. Just recently the more comprehensive marine spatial plan has been accepted and the designated sectoral preference areas are now legally binding. Although the preference areas for wind resource development have been designated, concrete wind farm constructions plans within those areas have to be approved on an individual basis. For the German EEZ and adjacent coastal waters we developed a spatial explicit integrated modelling approach accounting for the distribution patterns of the commercially important resource plaice, the activity pattern of the fishing fleet targeting plaice, the revenues generated in the areas of interest, and the spatial extent of renewable energy development such as wind farms. We developed a Bayesian Belief Network – GIS framework to assess potential consequences of different spatial management scenarios which describe different options for the level of offshore wind resource development, designation of conservation areas and the related fishing effort displacements. With the help of the BN-GIS framework we explored in particular the risks for an increased vulnerability of plaice to fishing pressure and the consequences for the fishing revenues.

Key-words: Bayesian Belief Network, fishing effort, GIS, plaice (*Pleuronectes platessa*), regression kriging, spatial management, windfarm development

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1 Introduction

The worldwide increase in the number of marine uses and their demand for sea space increase the pressure and impact on marine ecosystems (Halpern et al., 2008). This calls for integrated and ecosystem based spatial management approaches allowing a sustainable development of marine resources while safeguarding marine environmental health (Leslie & McLeod 2007, Ruckelshaus et al. 2008). In Europe the marine strategy framework directive (MSFD) is a legal framework in which member states are obliged to achieve or maintain good environmental status in the marine environment by the year 2020. Thus the high level objectives of the MSFD are clean, healthy and productive seas while promoting the sustainable use of marine resources. The practical implementation of the MSFD comprises a sequence of evaluation processes accounting for an array of ecosystem components and pressures. One spatial explicit management approach that aims to balance management objectives is marine spatial planning (MSP). MSP is a public process of analyzing and allocating the spatial and temporal distribution of human activities in marine areas to achieve ecological, economic, and social objectives that usually have been specified through a political process (Douvere et al., 2007; Douvere, 2008). In a recent study by Foley et al. (2010) ecosystem based MSP is defined as an integrated planning framework that informs 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.

Two types of conflicts arise from the spatial management of human activities which are conflicts between the activities and the environment and conflicts between activities. The former type of conflict should be analysed using a risk based approach that assesses the impacts of human activities which vary in their intensities and footprint on ecosystem components that are sensitive to those activities. An increasing number of studies presented practical approaches to quantify impacts of specific human activities or cumulative impacts of numerous activities on ecosystem components (Ban et al. 2010; Halpern et al., 2008; Foden et al., 2010; Stelzenmüller et al., 2010). In the context of marine planning the impact of one human activity on other activities is studied to a lesser extent. One example is a study by Berkenhagen et al. (2010) were cumulative economic impacts for the fisheries sector are analysed due to the development of offshore wind energy in the German exclusive economic zone (EEZ).

As yet studies assessing spatial management options by integrating more than one sector and their potential impacts on both each other and ecosystem components are lacking. In general, environmental management is a multiple objective problem because there are a number of objectives and a range of possible management interventions. In land use management methods used to support multiple objective management encompass multi criteria analyses (MCA) or spatial optimization techniques such as Pareto optimality (see Kennedy et al., 2008; Polasky et al., 2008 and references therein).

Ecosystem based marine spatial management approaches such as MSP allocate the spatial and temporal allocation of resource use, therefore it is crucial to account for the uncertainty associated with the data used, and to visualise the uncertainty associated with the outcomes of possible spatial management scenarios. 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 (see e.g. Varis et al., 1990; Marcot et al., 2001; Nyberg et al., 2006). A recent study by Stelzenmüller et al. (2010) 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 here a BN-GIS framework to assess the potential consequences of spatial management options in the German EEZ and adjacent coastal waters. The maritime spatial plan for the German EEZ is legally binding and contains designated sectoral preference areas (BMVBS, 2009). The spatial plan specifies a number of high level objectives such as e.g. the promotion of offshore wind energy use (25000 MW by 2030) or protection of natural resources by avoiding disruptions to and pollution of marine environment. Moreover, the spatial plan contains a number of special areas of conservation (Natura2000 sites) with specific objectives such as the achievement and maintenance of a favorable conservation status as described in the EU Birds and Habitats directives (EU, 1992). Although the sectoral preference areas have been designated the individual wind farm licenses will be subjected to an environmental impact assessment and currently fisheries management options are assessed for the Natura 2000 sites (see Pedersen et al., 2009). This generates a number of future spatial management scenarios with different economic consequences for the sectors involved. Thus within the study area we used a BN-GIS modelling approach to assess the potential consequences of example spatial management scenarios due to wind farm development for a number of fishing fleets, the commercially important resource plaice and the revenues generated in the area of interest.

2 Material and methods

2.1 Bayesian Belief Network development

Our study area comprised the German EEZ of the North Sea with the adjacent coastal waters (Fig.1) and we used a vector grid with a resolution of 3nm for the subsequent analysis. This grid contained all of 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.

Average bottom temperature and average bottom salinity–Bottom temperature and bottom salinity are environmental predictor variables for plaice. From the oceanographic database of the International Council for the Exploration of the Sea (ICES) we extracted sea bottom temperature and salinity data for the years 2000 to 2009 for the third quarter of each year. Within the study area we interpolated the temperature and salinity values on a high resolution grid (0.6 nm or 0.01 decimal degrees), using ordinary kriging (Cressie, 1991), to represent the average bottom temperature and salinity. In a second step we summarized the values on the 3nm vector grid.

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 comprised the four 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).

Plaice total and Plaice 27 cm – For the study area we extracted survey catch data from the third quarters of 2000 to 2009 (393 tows) for plaice (*Pleuronectes platessa*) from annual beam trawl surveys deploying a 7 m beam trawl with a towing time of 30 min with the German research vessels SOLEA I and SOLEA II. With the help of a length-weight relationship (w [kg]= a length^b; a = 0.0069 and b = 3.1084; vTI data) we computed cpue (kg / 30 min) for total plaice catches and the size class ≥27 cm, as 27 cm corresponds to the minimum landing size of plaice. To account for the statistically significant ($p = 0.05$) inter-annual variability in plaice catch data (total and ≥ 27 cm) we standardized the cpue data with the help of generalized linear models (GLM) using the factor “year” as predictor variable. As described in Stelzenmüller et al. (2007) we derived calibration coefficients by back-transforming the parameter estimates (Quinn II and Deriso, 1999) and transformed cpue data by dividing the raw cpue by the appropriate power coefficient.

Hence, we conducted the subsequent spatial prediction of the average plaice distribution pattern with standardized and aggregated cpue data. We used regression kriging, a hybrid technique which combines regression techniques with kriging of the regression residuals (see details to the method in Hengl et al., 2007). Some recent studies used this modelling technique to estimate spatial distribution pattern of commercially relevant species such as plaice, sole (Solea solea) and thornback ray (Raja clavata) (Maxwell et al., 2009) or fishing effort density around marine protected areas (Stelzenmüller et al., 2008).

In a first step we assessed the relationships between cpue data of plaice (total and ≥ 27 cm) and the environmental variables (bottom temperature, bottom salinity, and depth) at the sampling locations using Generalized additive models (GAMs) (Hastie and Tibshirani, 1986). We computed Pearson product moment correlation between the cpue data and the environmental variables (bottom temperature, bottom salinity, and depth) and among the environmental variables to detect co-linearity. Further we allowed for possible non-linear effects of the environmental variables using natural splines (Venables and Dichmont, 2004) while controlling the risk of over fitting by limiting the degrees of freedom. From the full set of calculated GAMs, we selected the best models by the lowest value of Akaike Information Criterion (Akaike, 1973). Using the selected models we predicted for each year total plaice cpue and plaice ≥ 27 cm log (1+cpue) for each grid cell of a high resolution grid (0.6 nm).

Subsequently, we corrected the GAM estimates by conducting a geostatistical analysis of the GAM residuals which is the second step of the regression kriging process. We described the spatial structuring of the GAM residuals using semivariograms and fitted parameters of spherical models (nugget effect, sill and range) with a weighted least squares fitting procedure (Cressie, 1991). Afterwards we predicted for each grid cell of the high resolution grid (0.6 nm) a value of the residuals using ordinary point kriging. We then combined the respective trend and autocorrelation maps to produce continuous maps of the respective plaice catch data. In final step we transferred the predicted cpue of plaice (total and ≥ 27 cm) to the standard vector grid (3 nm).

Fishing effort, FEBeam, FEOtter, FEShrimper – As an example we used German VMS (vessel monitoring system) and logbook data from 2008 to determine high spatial resolution (3 by 3 nm miles) fishing effort and total catch (marketable catch). Original VMS data consist of the vessel identification number, position, speed and heading. Fishing effort was calculated for the métiers with bottom contact and which potentially catch plaice ≥27 cm. Thus we summarized beamtrawls fishing for brown shrimp, mesh size 16 to 31mm (referred to as FEShrimper), and beamtrawls (referred to as FEBeam), and otterboards fishing for flatfish, mesh size >=80mm (referred to as FEOtter) and the total fishing effort is referred to as “Fishing effort”. In a first step, data were filtered for “fishing” and “not fishing” using the speed of each vessel individually, i.e., a certain range of low speed was labeled “fishing” whereas higher speed and standing still were labeled “not fishing”. The position of the boat was then allocated to a 3 times 3 nm miles rectangle (i.e. 100 fine rectangles per ICES rectangle) and the time interval between two positions was summed up to the amount of fishing effort spent in a specific 3 times 3 nm rectangle (hours fishing). Since the time interval between each position can be up to two hours there is a considerable portion of 'unseen' activity by each vessel. The method applied, here, for VMS data analysis takes account of this uncertainty by substituting each registration with a discrete set of positions with high probability of vessel presence (see details in Fock, 2008).

Total catch and Euro – We derived the total catch from landings of plaice indicated in the logbook data. We aggregated landings according the VMS data and calculated the total catch (kg) for 2008. The total catch was distributed proportionally to the effort to the specific 3 times 3 nm rectangles. In a final step the catch was multiplied by the mean price (1.89 €) of plaice of German landings in 2008 to calculate the revenue (referred to as Euro) gained in 3nm grid cell.

Vulnerability – The vulnerability of plaice ≥ 27 cm to fishing is defined as:

$$\frac{cpu_{\ i}}{\sum_i \ \ cpu} \Big/ \frac{Total\ catc_{\ i}}{\sum_i \ \ Total\ catc},$$

with the first term reflecting the modeled 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. The lower the calculated value, the higher is the degree of vulnerability for plaice ≥ 27 cm. We then transformed the vulnerability values ranging from 0 to 1680 to six vulnerability states using quantiles (state1 (0) = no ; state 1 (60 - 1680) = very low; state 2 (22 - 60) = low; state 3 (5 - 22) = intermediate; state 4 (0.4 – 5) = high; state 5 (0.04 - 0.4) = very high).

The BN was developed using the Netica software system (www.norsys.com) (see details on the inference algorithm implemented in Netica in Spiegelhalter and Dawid, 1993). 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 from each other. Each parent node has different discrete states (e.g. temperature or depth categories) with an associated probability of occurrence. The FEBeam, FEOtter, FEShrimper nodes, 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 this 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).

2.2 Marine management scenarios

The aim of this study was to assess the potential consequences of spatial management scenarios on the vulnerability of the resource to fishing and the revenues generated from plaice catches using the BN-GIS framework. Thus after building and testing the BN as described above, we used it to infer the behaviour and response of the variables to different management scenarios. We defined two 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 as management objective to maintain the current vulnerability of plaice to fishing. We simulated an increase in the relative average bottom temperature in our study area (state 1: 10.6 %, state 2: 10.6%, state 3: 15 %, state 4: 32%, and state 5: 32%) and predicted the potential consequences for vulnerability. We then predicted a possible management intervention for the total fishing effort to maintain the current measure of vulnerability of plaice.

Scenario 2 - How does the vulnerability of plaice change after the development of offshore wind farms and a related displacement of fishing effort? One of the high level objectives for the German marine spatial management is an installed capacity of offshore wind energy of 25000 MW by 2030. We used the current application areas for wind farms (provided by BSH) to construct a fishing effort displacement scenario (see Fig.3). We reset the fishing effort for grid cells within the application areas to zero and redistributed the same amount of fishing effort. For the displacement scenario we constructed in the GIS three buffer rings (3, 10 and 15 km) around the application areas and redistributed the fishing effort of the respective fleets with 70 % of the effort to the 3 km buffer area, 20 % to the 10 km buffer area, and 10% to the 15 km buffer area. This displacement scenario should account for the fact that fisher men 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).

3 Results

3.1 Baseline scenario

The complete model derived describing the relationships between fishing effort, total catch of plaice, environmental parameters and the distribution of the resource is presented in Figure 4. Under the current fisheries management and the predicted spatial distribution of the resource we computed that 18.6 % of the area experienced a vulnerability of 0 (state 1) and 32.6 % of the area are in vulnerability state 4 (high). The revenue node (Euro) showed that 18.8 % of the area generates between 37 and 210 € from German plaice landings in 2008. The fishing effort of the fleets revealed that their main activity took place on roughly 50 % of the study area. The baseline scenario also revealed that only 13% of the area generated German plaice catches between 600 and 9600 kg.

3.2 Scenario 1

The consequences of the simulated increase in average bottom temperature from 13.9 °C to 14.4 °C are displayed in Figure 5a. The average vulnerability of plaice increased from 2.34 to 2.43 caused by a marginal increase of surface area being in vulnerability state4 and a slight reduction in surface area with vulnerability state 0 and 1. This increase in the average vulnerability is not significant as it is still in the confidence limit of the standard deviation. However to maintain the current average value of vulnerability one possible management option would be to increase the number of cells in fishing effort states 1,2 and 3 by 10% and reduce the cells in fishing effort state 4 and 5 by 14 % (see Figure 5b). This option would affect the FE Shrimper fleet most as the number of cells in state 1 (low FE Shrimper effort) need to be increased from 50 % to 70 %. The consequences for the revenues would be a possible increase of the mean catch by 100 kg to 865 kg with an associated increase in mean revenue per grid cell area of 230 €.

3.3 Scenario 2

The model predicted all states of the total catch and vulnerability based on the simulated distribution of fishing effort after the closure of the wind farm application areas to fishing. As an example the spatial pattern of the current vulnerability states 0, 3 and 4 are compared to the predicted probabilities for a grid cell to be in a certain vulnerability state after the displacement of fishing effort given the same spatial distribution of the resource (Figure 6). The spatial pattern of the predicted probabilities of vulnerability state 0 showed that a distinct smaller area (with values between 0.8 and 1) in the northern part of the study area. Overall the number of grid cell with a probabilities ranging from 20 % to 50 % to be in vulnerability state 3 increased compared to the actual pattern of cells in vulnerability state 3. The pattern of the predicted probabilities of vulnerability state 4 showed distinct deviations from the current pattern in the northeastern part of the study area. Thus this indicates a decrease of the vulnerability in those cells.

4 Conclusions

Results showed the great potential of the application of the BN-GIS modelling framework to address a range of management objectives and interventions. Moreover this approach allowed us to examine the spatial pattern of uncertainty related to marine management scenarios which is very important in a marine planning context where conflicts between human activities may need to be resolved. As any modelling technique the BN-GIS framework constructed to describe complex relationships between human activities and sensitive ecosystem components is constrained by the available geodata at the relevant spatial scale. The scenario outcomes reflect options for management targets and consequences of spatial management interventions rather than final solutions. For instance the assumptions made for the fishing effort displacement scenario have already an impact on the scenario outcomes. Thus future applications of our framework should consider international data for fishing effort, total catch and revenues to address the cross-boundary consequences of spatial management options in German waters. Once the drivers of the fishing effort allocation are understood those components may be included in future studies to improve the development of fishing displacement scenarios and to derive more realistic estimates of potential consequences. We conclude that the BN-GIS framework can be a useful tool to support the decision process by helping to provide informed decisions, through the assessment of potential outcomes and related uncertainty from management measures in a spatial context, and to offer a visualisation tool that facilitates the engagement of different stakeholders in such a process.

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Figure 1

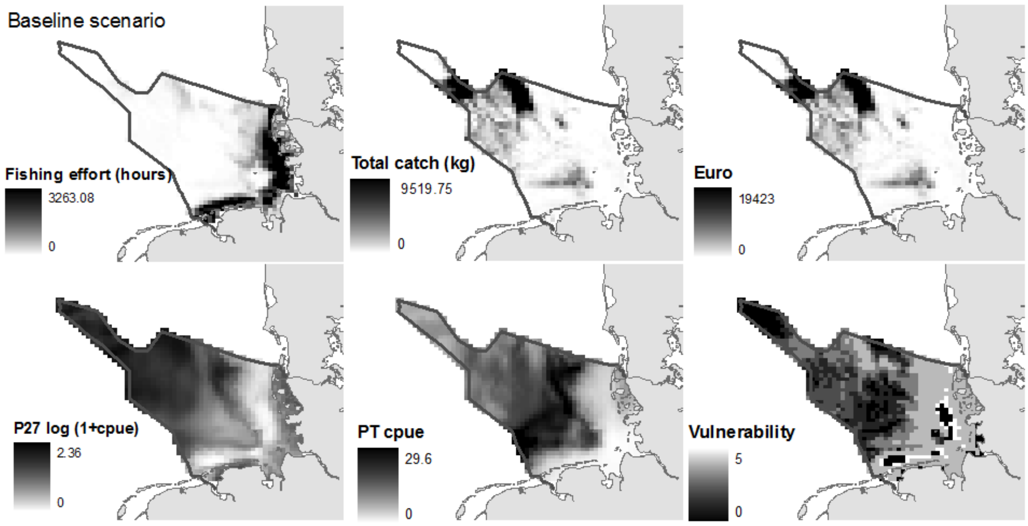

Figure 1: Study area with spatial distribution pattern of the total fishing effort in 2008, the total catch (kg), revenue (Euro), plaice ≥ 27 cm and total plaice cpue (predicted with regression kriging) and the measure of vulnerability (0 - 5).

Figure 2

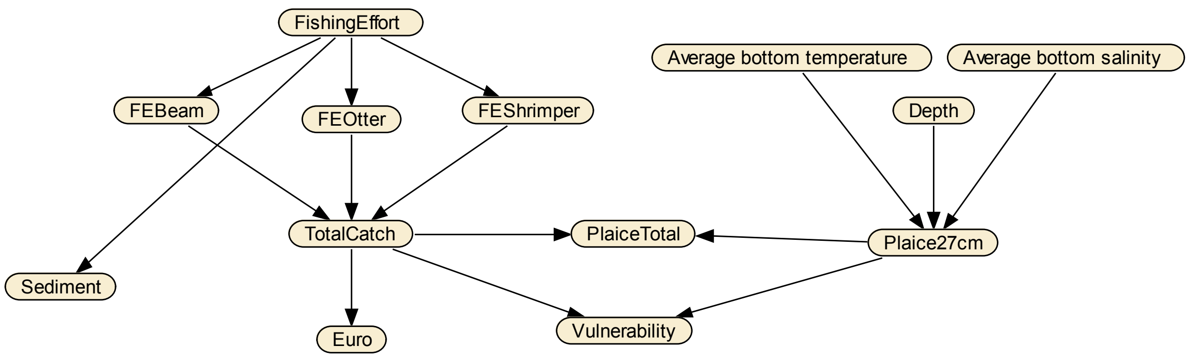

Figure 2: Conceptual model showing the key variables used to predict the overall level of vulnerability of plaice to fishing as a function of the total catch and cpue of plaice ≥ 27 cm.

Figure 3

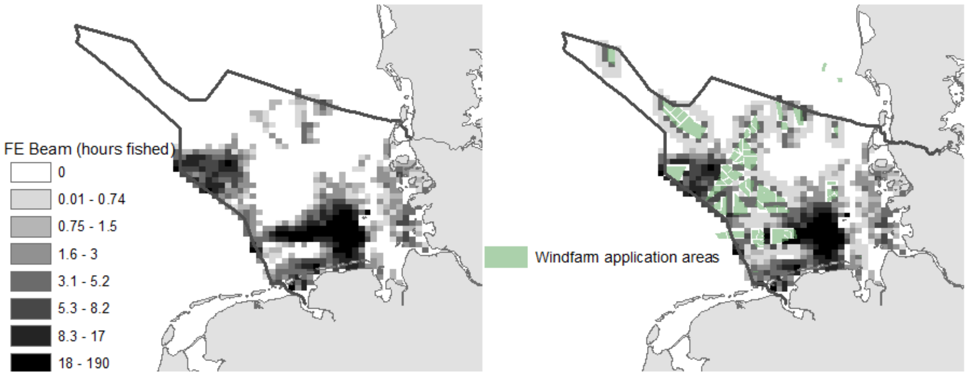

Figure 3: Spatial distribution pattern of beam trawl fleet (FE Beam) (left) and respective fishing effort displacement scenario for the beam trawl fleet (right).

Figure 4

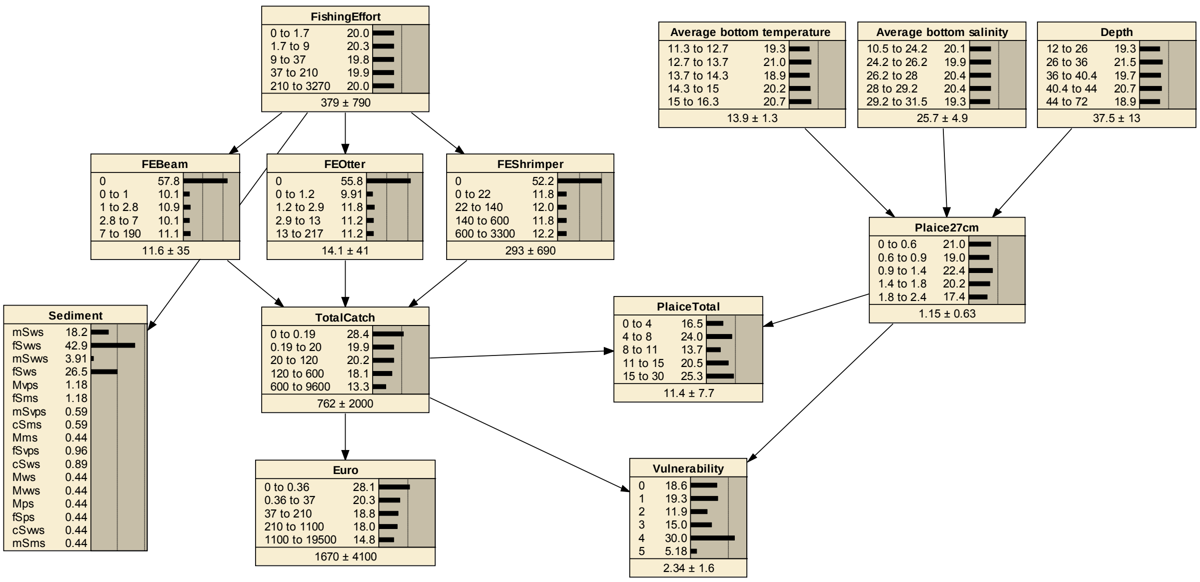

Figure 4: Results of the baseline scenario.

Figure 5a

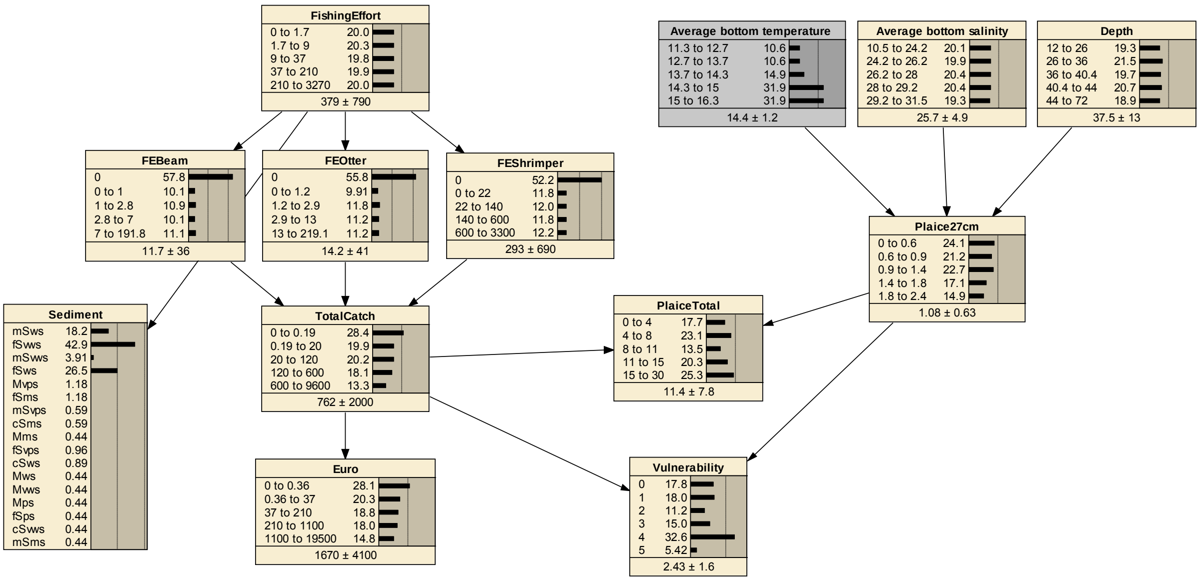

Figure 5b

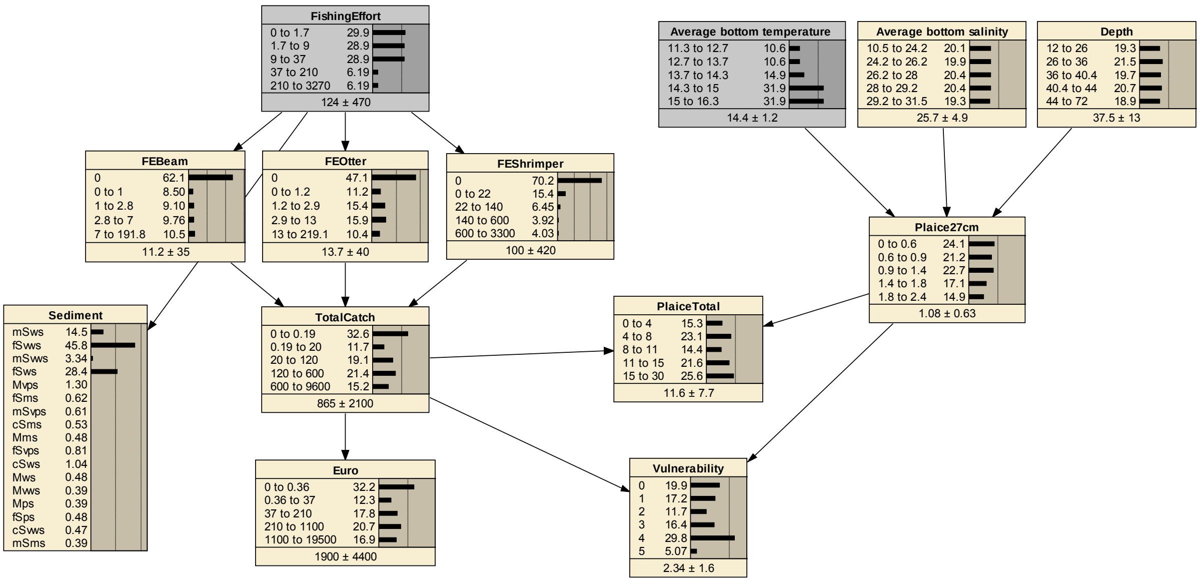

Figure 5a and 5b: The model results of scenario 1 after simulating the increase in temperature (top) and adapting the fishing effort to maintain an average vulnerability measure of 2.34 (bottom).

Figure 6

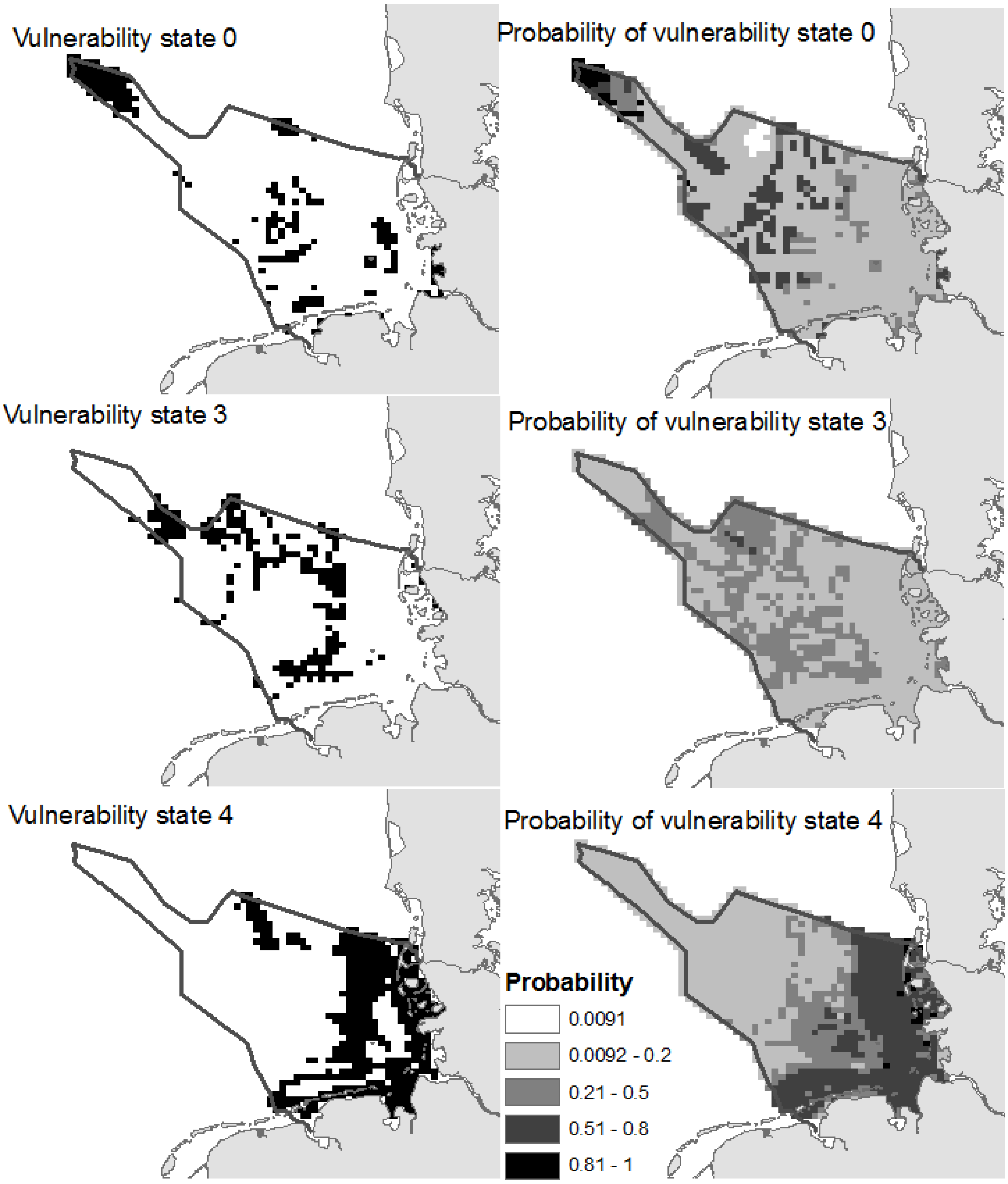

Figure 6: Results for scenario 2 on the assessment of changes in vulnerability states after the closure of windfarm application areas to fishing together with a displacement of fishing effort. The current distribution of cells in vulnerability states 0, 3 and4 (left) and the predicted probabilities for the vulnerabilities states 0, 3 and 4 (right).