From fish biodiversity indicators to spatial risk assessments -Towards the integration of Blue Growth and conservation objectives in the German Bight

Dissertation

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Spatial management measures are increasingly implemented in the Southern North Sea which is one of the most intensively used marine areas in the world. Various human activities are competing for space while exerting chronic pressures on marine habitats and the associated fauna. The most dominant spatial conflict exists between the development of offshore wind farms (OWF), conservation interests and the fishing sector. The effects of spatial allocations such as for OWF development or the designation of Natura 2000 sites as well as resulting displacement of fishing effort on benthic systems are riddled with uncertainties.

The policy landscape governing spatial management processes is likewise highly complex. One of the future governance challenges in European seas will be to align economic growth from the sea ("Blue Growth") with conservation of biodiversity and ecosystem health. Amongst the key policies that members states of the European Union need to conform to is the Marine Strategy Framework Directive (MSFD) which requires achieving good environmental status (GES) of European seas. In addition, member states need to implement maritime spatial plans under the Maritime Spatial Planning (MSP) Directive to achieve sustainable use of marine resources. Both instruments aim at implementing an ecosystembased spatial management approach. However, a current gap is the lack in spatially explicit indicators and associated management targets that could describe the achievements towards multi-objective planning. In addition, holistic assessment procedures are lacking which facilitate information needs of policy objectives and allow evaluating risks, opportunities and uncertainties of spatial management options on the ecosystem.

The aim of this dissertation is thus i) to perform such an assessment by operationalising spatially explicit indicators of fishing pressure and ecosystem state and ii) to synthesise information in a risk based probabilistic approach (Bayesian Belief Networks) that allows testing trade-offs and uncertainties of planned spatial management measures. The analysis is performed in the German Bight, specifically the Exclusive Economic Zone (EEZ) of the North Sea, focussing on benthic communities, mostly demersal fish.

Chapter 1 of this thesis introduces the marine policy landscape in Europe and marine spatial management in the German Bight. This includes a scoping analysis on common goals and operational objectives between Blue Growth and the current conservation legislation. In the

absence of such objectives and specific management targets, the protection of marine biodiversity was identified as main cross-cutting theme.

Ecosystem-based spatial management requires spatially explicit, operationalised indicators. However, mapping of biodiversity indicators at the community-level is not trivial. Hence, **Chapter 2** provides a methodological comparison of two dominant mapping approaches. Further, a straight-forward method (the mean value approach) is proposed for dealing with rare species that could otherwise not be modelled due to zero-inflated data and to address sampling issues inherent in biodiversity indices. Finally, a novel indicator, the community sensitivity index to fishing (CSI) is developed, which is based on life-history traits and was designed to quantify how sensitive a community is to additional fishing mortality. Both mapping approaches are applied to species richness, Hill's N₁ (combining both richness and abundance) and the CSI. While both approaches were conceived to be context dependent, the so-called indirect approach provides more comprehensive estimates of fish biodiversity and sensitivity in a European context. Results further suggest that biodiversity hot-spots with regard to demersal fish are not well conserved in the future Natura 2000 network, designated to preserve reefs, sand banks and key species.

Quantifying the relationships between fishing pressure, environmental drivers and biodiversity state has remained elusive in the past. In **Chapter 3** these relationships are tested looking at spatial patterns of the main international bottom trawling fleets and the previously mapped CSI to test whether the CSI could be operationalised for management advice. First, fishing effort was interpolated at the fleet level based on vessel monitoring system (VMS) data. A suite of regression-based techniques revealed a significant decline in index values with increases in fishing pressure with the coastal small beam trawl fleet. The CSI could thus be operationalised for this fleet. Responses in other areas were less clear or even reversed and mostly driven by environmental factors such as depth. Result stress the difficulty in quantifying precise pressure-state relationships in a chronically disturbed system and that further assessments should thus focus on risk-based approaches that look at relative rather than absolute changes.

Chapter 4 provides a comprehensive introduction into quantitative risk assessment standards. A meta-analysis of the current use of risk analyses in a spatial management context was performed and found much disagreement in the application of this concept. The risk concept was then applied to spatially quantify the risk of fishing effort displacement due to OWF developments; specifically looking at the vulnerability of the benthic community. This was described by a disturbance index (DI) defined as a ratio between relative local mortality

by demersal trawling fleets and recovery potential of benthic communities. The risk analysis was conducted by coupling a Bayesian Belief Network (BN) with a Geographical Information System and subsequently adapting the probability distributions of affected fishing fleets in the baseline model to reflect anticipated changes in fishing fleets. Results suggest that benthic communities would likely face an up to 8 % increase in risk of worsening DI values compared to the current state. In a MSFD context this would equate to not achieving GES.

Finally, in Chapter 5, a similar approach was applied to a suite of current and planned spatial management measures, namely OWFs, Natura 2000 reserves as well as the Plaice Box, to explore associated risks and uncertainties on fish biodiversity. Specifically, main cause-effect pathways were analysed between bottom trawling, environmental drivers and the CSI, species richness, as well as abundance of cod, which is a species of conservation concern in Germany. In contrast to the previous chapter, the BN models incorporated a set of empirically derived decision rules of fishing effort displacement, fishermen compliance with regulations, protection effects inside and spillover from areas closed to fisheries as well as different stages of OWF developments. Finally, temperature increases due to climate change were simulated, leading in total to ten short (5 year) and mid-term (15 year) scenarios being analysed. These included testing how much effort reduction of small beam trawls would be necessary until 2020 in order to achieve CSI values that were indicative of an intermediately sensitive community as a potential objective of reaching GES. Scenarios suggested that this would require up to 9 % reduction in mean fishing effort per grid cell. Scenarios also revealed that conservation effects through area closures outweighed negative effects from relocation of fishing effort but that non-compliance could locally hamper recovery. EEZ wide effects were only caused through a simulated change in temperature which led to an overall increase in species richness and abundance of cod but the CSI declined in 44 % of the area. Conservation success will thus also depend on factors that are not controllable by management with differing risks and opportunities for the recovery of species and communities potentially overriding management actions.

Chapter 6 synthesises thesis results and discusses remaining research needs. Taken all together the thesis provides a comprehensive analysis of the spatial management system in place and its likely effects on future trends on fish biodiversity. Spatial BNs provide a very useful tool to look at the range of possible future outcomes, risks and uncertainties by simulating management scenarios. BN results were heterogeneous in different areas of the German Bight emphasising the importance of spatially explicit analyses. Besides the

remaining bottlenecks in the operationalisation of biodiversity indicators the analysis stressed the importance of understanding not only the direction of cause-effect pathways but also its dynamic as well as the influencing factors. This will require dedicated empirical research to close gaps in current mechanistic understanding of single and cumulative effects of fishing and OWFs on marine biodiversity. While the results suggested that no large scale decline in fish biodiversity would result from fishing effort displacement, analyses need to include activities of neighbouring countries in the future. Such trans-boundary assessments are not only required by the MSFD and the MSP Directive, they are also important to address combined effects of spatial management measures in the North Sea as well as the crossborder nature of populations and habitats. We are still changing the marine environment at a quicker pace than the understanding that we have to truly achieve sustainable management of resources. In combination with large uncertainty of climate change effects, managers should therefore embrace the precautionary principle instead of hoping for specific management targets. Until now MSP in Germany is characterised through ad hoc planning with a clear emphasis on OWF developments and Blue Growth in general rather than incorporating adaptive science to achieve sustainable development.

In order to achieve a real integration between Blue Growth and conservation political will needs to prioritise both elements at least equally. Further, it is up to scientists to make a stronger case for science-based decision making and bridging the science-policy interface by adapting models to reflect practical management relevant issues. Finally, we as a society need to decide upon the kind of sustainability that we want for our future.

Chapter 1

General introduction

1. The challenge ahead: Integrating Blue Growth with conservation objectives

The North Sea is one of the most productive and intensively used shelf seas in the world due to its strategic location, where various types of human activities are competing for space (Ducrotoy et al. 2000; Emeis et al. 2015). Commercial fisheries, shipping, aggregate mining and oil and gas drilling are among the more traditional uses. The need for safe and renewable energy as well as economic growth and jobs has instigated a harnessing of economic potential of marine environments, coined as "Blue Growth", which was set out in the EU Integrated Maritime Policy (IMP; EC 2007) and reaffirmed in the Europe 2020 Strategy in 2010. Marine aquaculture and offshore wind farms (OWF) are among the emerging uses. Especially the development of OWFs has proliferated and has become a policy priority for Blue Growth as described in the EU Strategic Energy Technology Plan (SET-plan). In Europe, 3589 grid-connected wind turbines had been installed by the end of 2016, generating more than 12,6 GW (Pineda & Tardieu 2017).

Blue Growth is said to be the main strategy to support sustainable growth in the marine and maritime sectors (EC 2012), but how sustainable current and planned marine economic activities really are is a matter of debate. It is for example contested, how "green" the immense development with OWFs actually is, given that these structures have a bearing on the hydrography, produce electromagnetic waves and noise and may disrupt a soft bottom dominated environment potentially compromising the integrity of the ecosystem (Wilhelmsson 2010; Gasparatos et al. 2017). These aspects may be balanced by providing refuge for species through the exclusion of fishing effort (Hammar et al. 2016). In addition, Europe is in the process of implementing the largest marine reserve network (Natura 2000) to date. Both, OWFs and marine reserves exclude or restrict fisheries. This will cause a considerable displacement of fishing activities potentially leading to unsustainable use in remaining open areas (Bastardie et al. 2014). Bottom trawling remains the largest threat for demersal species and habitats and makes up 99 % of the spatial footprint of human activities in UK waters (Foden et al. 2011). To date, many vulnerable habitats such as Sabellaria and Lophelia reefs have been decimated (Holt et al. 1997; Gilbert et al. 2015). Currently, half of the commercially exploited fish stocks are not within safe biological limits (EC 2015) and a shift from historical dominance of larger, commercially valuable species to smaller, more productive species of lower commercial value is apparent (Sguotti et al. 2016). In German waters of the North Sea, alone 27 % of fish species are listed as threatened or extinct under the national Red List and only 43 % are classified as unthreatened (Thiel et al. 2013). In addition, climate change steers us into an uncertain future causing changes to and shifts in fish community compositions (Dulvy et al. 2008). Therefore, the big challenge ahead, much like in other parts of the world, will be to balance Blue Growth and marine conservation objectives to truly achieve sustainable use of marine resources.

2. The solution? EU policies to achieve Ecosystem-Based Marine Spatial Management

The European policy landscape is highly complex (Bigagli 2015). More than 200 legal instruments are making provisions for the (sustainable) use and /or conservation of the marine environment in Europe (Beunen et al. 2009). With the implementation of the Integrated Maritime Policy (IMP) ten years ago the EU has set out to integrate ocean policies aiming at promoting a coordinated governance of the different activities and interests related to the seas (Fritz & Hanus 2015). In addition, a paradigm shift is taking place from policies addressing management of single components to an integrated Ecosystem-Based Management (EBM) system aiming at sustainable development. EBM takes into account "*interactions among ecosystem components and management sectors, as well as cumulative impacts of a wide spectrum of ocean-use sectors*" (Rosenberg & McLeod 2005). Essentially, EBM considers humans as an integral part of the ecosystem, acknowledging that we can only manage our own actions instead of the ecosystem itself (Rogers & Greenaway 2005; Levin et al. 2009).

Given that the spatial component is inherently critical in the concept of EBM, spatial management approaches such as Marine or Maritime Spatial Planning (MSP) are being advocated to support Ecosystem-Based Marine Spatial Management (EB-MSM) (Gilliland & Laffoley 2008; Ehler & Douvere 2009; Katsanevakis et al. 2011) while resolving intersectoral and cross-border conflicts over maritime space. In fact, the EU has termed MSP to be the most important cross-cutting process to implement EBM and thus facilitate sustainable development (EC 2008a). MSP "*is a public process of analysing and allocating the spatial and temporal distribution of human activities in marine areas to achieve ecological, economic, and social objectives that are usually specified through a political process"* (Ehler & Douvere 2009).

MSP initiatives are being increasingly implemented worldwide; however driven by different priorities. In some places, for instance Australia, conservation (the establishment of marine

reserve networks) has been the main driver behind MSP, whereas in Europe there is a clear sectoral focus to achieve Blue Growth (Collie et al. 2013; Qiu & Jones 2013). Large scale OWF development plans have accelerated the race for space at sea and have let several European countries such as Belgium, the Netherlands and Germany to implement national plans to resolve inter-sectoral conflicts and establish investment security (Douvere & Ehler 2009). Nature conservation is seen as one among several sectoral interests.

Key elements of MSP are an adaptive management process in which a plan is implemented, monitored and progress is evaluated towards achieving specific spatial management objectives (Douvere & Ehler 2011) (Fig. 1). Maritime spatial plans are ideally drafted with major input from stakeholders or the public, supported by adaptive science throughout the process of decision making and revisions of the plan (Pomeroy & Douvere 2008; Olsen et al. 2014). MSP therefore has the potential to integrate the public and policy domain, science and managers (Ehler & Douvere 2009).



Fig. 1. Conceptual MSP process (Ehler and Douvere, 2009)

To firmly root MSP in EU policy, the Maritime Spatial Planning Directive (MSPD; EC 2014) was implemented in 2014 which requires all member states with access to the sea to put forth maritime spatial plans until 2021. These plans have to be revised every ten years. However, no provisions for monitoring are made. Member states are however required under other directives to carry out a Strategic Environmental Assessment (SEA; EC 2001) of impacts from implementing MSP as well as Environmental Impact Assessments (EIA; EC 1985) for activities that can be regulated under the MSP such developing OWFs prior to approval.

The single most comprehensive instrument to marine conservation and EBM is the EU Marine Strategy Framework Directive (MSFD; EC 2008b), the environmental pillar of the IMP, which promotes healthy ecosystems and requires member states to achieve or maintain "good environmental status" (GES) of their seas by 2020. The aim is to *"prevent and reduce inputs in the marine environment [...] so as to ensure that there are no significant impacts on*

or risks to marine biodiversity, marine ecosystems, human health or legitimate uses of the sea" (Article 1). This entails the development and implementation of marine strategies in order to "protect and preserve the marine environment, prevent its deterioration or, where practicable, restore marine ecosystems in areas where they have been adversely affected". GES is described through 11 descriptors which extend established management themes such as commercial fish stocks and eutrophication to novel fields of marine litter and energy & underwater noise (Box 1). The MSFD is organised on the principle of subsidiarity, enabling member states to implement the directive in accordance to their national situation. The MSFD follows a six year adaptive process, which started with the initial assessment of the status of the seas (Art. 8 MSFD), the determination of GES (Art. 9 MSFD), and the establishment of environmental targets (Art. 10 MSFD) which each member state had to carry out and submit to the EC in 2012. Based on criteria and indicators under each descriptor and the methodological standards described in the Commission Decision (EC 2010), member states had to set up a monitoring programme until 2014 (Art. 11 MSFD), followed by a programme of measures (PoM) in 2015 (Art. 13 MSFD), to be implemented in 2016 in order to achieve or maintain GES. Special reference was made to "spatial protection measures, contributing to coherent and representative networks of marine protected areas". Both programmes had to incorporate existing monitoring programmes, assessments or management measures and reflect the national situation but should also add to this in case of gaps (EC 2008b).

Box 1. The MSFD process (wwf.org.uk) and eleven descriptors (D) that define the areas that need to be addressed in order to reach or maintain GES until 2020 and for which monitoring and management programmes had to be implemented.



Stakeholders have proposed MSP as a means to assist with MSFD implementation to reach GES (EC 2011). The MSPD will contribute, inter alia, to achieving the aims of the MSFD (Preamble 15) as well as the EU Biodiversity Strategy to 2020 (EU 2011). MSP linkages are indirectly embedded in the MSFD's programme of measures, which can include spatial and temporal distribution of human activities and the implementation of a coherent network of marine reserves. However, how this link can be put into practice is not yet clear.

As shown in table 1, the main difference between both directives refers to their priorities which are circled around conservation on one side and economic growth on the other. It also shows that both have adopted similar management concepts that are adaptive, precautionary, ecosystem-based and build on the notion of sustainable management of resources. It has generally been accepted that sustainability encompasses economic, social and environmental aspects. However, while the MSFD considers the environment to be the foundation of society's well-being, the MSPD considers this to be the economy (Qiu & Jones 2013). Nevertheless, there are opportunities to bridge both instruments; MSP could help implement the MSFD programme of measures through a concise planning and prioritising of activities. In return, monitoring under the MSFD could provide MSP with relevant (spatial) information for the planning process, e.g. to review the plan and assess its impact on the environment.

Table 1. General differences and similarities between the MSPD (Maritime Spatial Planning Directive) and the MSFD (Marine Strategy Framework Directive), as well as potential links between both Directives (printed in bold) (GES: Good Environmental Status; MPA: Marine Protected Area; EBM: Ecosystem-Based Management; EC: European Commission; DG: Directorate-General; EIA: Environmental Impact Assessment).

		MSPD	MSFD	
	Goal	Achieve Blue Growth	Achieve GES until 2020	
	Focus	Short term	Long term	
es	Grounds for sustainability	Economic growth	Conservation	
enc	MPAs	Sectoral (non)use	Foundation of EBM	
fer	Driver	Offshore wind energy sector	Conservation	
Dif	EC Directorate	DG Mare	DG Environment	
	Value system	Utilitarian values	Eco-centric values	
	Spatial management	Priority & reservation areas	May include spatial measures	
	Monitoring	Only project specific (e.g. EIA)	To be established by member	
		& review of plan every10 years	states	
	Ecosystem-based approach			
es		Sustainable use of resources		
riti		Precautionary principle		
nila		Adaptive management cycle		
Sin		To be implemented nationally with trans-national cooperation		
		Restoration of ecosystem components & habitats		

The relationship between MSFD and MSP has been discussed by authors quite controversially (Qiu & Jones 2013; Brennan et al. 2014; Gilbert et al. 2015; Maccarrone et al. 2015) and it needs to be tested whether an actual spatial plan focussing on sectoral interest can provide EB-MSM to assist with conservation goals of the MSFD.

Other key instruments with relevance for EB-MSM, conservation and Blue growth are the Habitat Directive (HD; EC 1992) and Birds Directive (BD; EC 2009), under which member states had to devise Marine Protected Areas (MPA; Special Area of Conservation and Special Protection Areas) as part of the Natura 2000 network. This included the implementation of management plans to achieve a *favourable conservation status* of sensitive habitats (Annex I) and key species such as marine birds and mammals (Annex II) by 2013. These management plans can include a restriction or complete ban of fishing activities (Fock 2011b). The Water Framework Directive (WFD; EC 2000) is responsible for land-based water bodies and transitional waters up to the 12 nm zone, excluding groundwater. Fishing is managed under the Common Fisheries Policy (CFP; EC 2013) since the 1970s giving all European fishing fleets equal access rights to EU waters and fishing grounds. The aim of the CFP, which is reformed every 10 years, is to secure jobs and facilitate food security by achieving maximum sustainable yield of target stocks. Temporary or permanent (partially) closed areas can and have been established under the CFP such as the Cod Box (Dinmore et al. 2003) and the Plaice Box (Pastoors 2000). More recently real time closures have also been implemented in some European countries which are short term closures that allow for a more immediate protection of fish stocks especially juveniles (European Parliament 2015).

3. The case study: Setting the spatial management context in the German Bight

All of the above mentioned directives require or encourage cross-border collaboration and integrated assessments at sea basin levels to implement EB-MSM. However, first and foremost obligations have to be implemented nationally. As a case study this thesis focusses on the management system in the German Bight, specifically in the German Exclusive Economic Zone (EEZ) of the North Sea. MSP in Germany is based on the German Spatial Planning Act (Raumordnungsgesetz), responsible for land-based planning which was extended to national marine waters up to 200 nm¹ in 2004, however retaining responsibilities

¹ The EU is signatory to the United Nations Convention of the Law of the Sea (UNCLOS), an international agreement from 1994 defining the rights and responsibilities of nations with respect to their use of the world's oceans. Under UNCLOS national waters are classified into the territorial sea up to a limit of 12 nautical miles (nm) from a 'baseline' (normally the low water line) and the Exclusive Economic Zone (EEZ) extending beyond these 12 nm up to 200 nm from the baseline of the territorial sea.

of the federal states ("Länder") for their territorial sea areas until 12 nm from the low water mark (Fig. 2). In total, Germany has five maritime spatial plans, three in the territorial seas and two in the EEZ of the North Sea and Baltic Sea. The maritime spatial plan in the German EEZ of the North Sea is legally binding since 2009 (Bundesministerium für Verkehr 2009) and was initiated after a wave of applications for OWF developments to avoid spatial use conflicts particularly between OWFs, shipping and nature conservation. Despite the environmental imperative of the plan, it came together quite ad hoc with very little scientific input such as the assessment of environmental impacts of different planning options (Jay et al. 2012). As part of the plan, priority and reservation areas have been designated for certain sectors in which other uses can be excluded. Priority and reservation areas for OWF and shipping have been implemented as well as various gas and oil pipeline corridors and gates for cable corridors for wind energy schemes. In addition, reservation areas for scientific research were designated. But areas for different uses are neither necessarily exclusive nor obligatory, i.e. OWFs were approved and developed outside of priority areas as long as they did not interfere with shipping lanes or Natura 2000 sites. The latter were included in the plan for information purpose only, along with licensing areas for sand and gravel extraction and military exercise sites (Jay et al. 2012). Much like in other EU countries, fishing is not integrated in MSP. Two reasons were given for not including fishing areas: First, data on spatial demands of fish and fisheries could not be provided in a way adequate for MSP purposes (Fock 2008). Secondly, the fishing sector felt that priority fishing areas would not suffice in harvesting migratory fish stocks and any spatial regulation would infringe of their access rights (Jay et al. 2012).

Fishing access is however denied under the CFP for large beam trawls defined as vessels with > 221 kW in the Plaice Box spanning coastal and further offshore areas of Germany, the Netherlands and Denmark. This MPA was implemented during the 1980s to protect nursery areas of plaice (*Pleuronectes platessa*). Under the HD, three Natura 2000 sites had been designated in the German EEZ of the North Sea in 2007, spanning about a third of the area. Specific management plans should have been implemented already in 2013 which has led the EC to instigate infringement procedures against Germany. The latest version of these management plans makes specific fleet and gear based provisions for the international fishing fleet. While bottom trawling, the most prominent fishing activity in the Southern North Sea, will be forbidden or restricted year-round, there will be less restrictions for static gears (BMUB 2016).



Fig. 2. Geographical scope and competencies of selected European legislation upon which measures of the MSFD relies (CFP: Common Fisheries Policy; EIA: Environmental Impact Assessment Directive; HD: Habitats Directive; MSP: Maritime Spatial Planning (Directive) (with specification for countries with separate MSP for territorial seas and EEZ: Exclusive Economic Zones); MSFD: Marine Strategy Framework Directive; SEA: Strategic Environmental Assessment Directive; WFD: Water Framework Directive (achieve good ecological status out to 1 nm and with extension out to 12 nm for good chemical status)). Adapted from Boyes et al. (2016).

The MSFD suggests incorporating additional MPAs to achieve a coherent network of MPAs. In Germany, it was concluded that existing or planned protection under the Trilateral Cooperation on the Protection of the Wadden Sea and the Natura 2000 network would suffice to reach GES even though the initial assessment of the status of the seas (Art. 8 MSFD)² it was concluded that German waters were not meeting GES. The MSFD Programme of Measures (PoM)³ however states the "inclusion of species and biotopes that define the value of an ecosystem in national MPA ordinances" as one measure to conserve biodiversity.

Figure 3 describes legal ordinances to protect species and habitats that could be used as basis for this MSFD measure.

^{2,3} www.meeresschutz.info/berichte-art13.html (retrieved March 2017)



Fig. 3. Timeline of ratification or implementation of national (in bold) and international legal ordinances, action plans and programmes that make provisions to conserve habitats, species and biodiversity that apply to Germany: Germany is party to the Convention of Biological Diversity (CBD) since 1992, which requires member states to develop National Biodiversity Strategy Action Plans (CBD NBSAP) which Germany implemented in 2007. This National Biodiversity Strategy includes more than 300 objectives; however, the marine environment is underrepresented. Germany is also signatory to various other international conventions such as the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) (with no bearing on German North Sea species), the Bonn Convention on the Conservation of Migratory Species of Wild Animals, the Bern Convention on the Conservation of European Wildlife and Natural Habitats and the Habitats and Birds Directive (HD & BD). National environmental protection laws (BNatSchG) are also in place. Natura 2000 refers to the designation of marine reserves under the HD and BD and MSFD PoM is the implementation of the Programme of Measures under the MSFD.

4. Evaluating effects of EB-MSM in the German Bight

As the previous sections elucidate, there is a complex policy landscape in place that aims to facilitate both Blue Growth and conservation objectives through the implementation of EB-MSM. Nevertheless, the operationalisation of this approach poses great challenges to the responsible management authorities given the level of integration of policies and crosssectoral management needed (Ansong et al. 2017). Hence, the practical implementation of EB-MSM remains first and foremost an institutional process (Cormier et al. 2017). However, information required for decision making in a multi-objective EBM context are far more extensive than in single-sector management. Naturally, assessment approaches also need to integrate a whole new set of components. Given that economic activities are intensifying and diversifying as is the management system governing these processes, likely effects and impacts need to be assessed to inform management. The adaptive sciences are in demand more than ever to support such evidence-based decision making by providing assessment procedures that allow evaluating risks, opportunities and uncertainties of spatial management options on the ecosystem (Mee et al. 2015). Indicators and models that can provide this are not always operational either (Leslie & McLeod 2007; Levin et al. 2009). Key information needs to operationalise EBM remain the "distillation of complex ecosystem information into digestible indicators; the establishment of reference levels on which management decisions *can be made; and clear protocols to evaluate tradeoffs*" (Link & Browman 2017) by means of risk analyses.

Various frameworks are proposed in the literature to evaluate risks of (spatial) EBM systems such as the Risk Assessment Framework described by Cormier (2013) or the Monitoring and Evaluation of Spatially Managed Areas Framework (Stelzenmüller et al. 2013). Under these frameworks risk components need to be specified and operational objectives set against which management targets can be evaluated. The outcomes of maritime spatial plans are however mostly broad goals rather than clear, measurable objectives (Collie et al. 2013). These goals need further translation into specific objectives that allow deriving appropriate indicators with assigned targets (Douvere & Ehler 2011). Operational objectives should be SMART, which stands for Specific, Measurable, Achievable, Realistic and Time-bound.

In the course of this thesis a literature review of the legislative texts and supporting documents of the MSFD and the German MSP was carried out to determine shared goals and operational objective between both instruments. Table 2 lists identified high level objectives of the German MSP and MSFD process. Overall objectives of the national German MSP are defined by 5 guidelines. Guidelines 1-3 of the German MSP are targeted at i) the promotion of sectoral uses via provision of investment security, ii) the avoidance of use conflicts, and iii) define shipping and OWF development as clear priority. Guideline 4 refers to the sustainable economic use of the sea via efficient planning and reversibility of uses, and finally guideline 5 refers to environmental protection. Therefore, all environmental targets of the German MSFD implementation as well as all MSFD descriptors are mainly linked to this guideline.

MSP	MSFD	
Five guidelines 1. Safeguarding and strengthening of maritime	Seven environmental targets 1. Seas unaffected by eutrophication	
traffic	2. Seas not polluted by contaminants	
2. Strengthening economic capacity through orderly spatial development	3. Seas with marine species and habitats unaffected by impacts of human activities	
3. Promotion of offshore wind energy use	4 Seas with sustainable and environmentally soun	
4. Long-term sustainable use of the features and	use of resources	
potentials of the EEZ through reversible uses, efficient use of space and priority of specific	5. Seas without pressures from litter	
marine uses	6. Seas not impacted by the introduction of	
5. Safeguarding the natural environment by	anthropogenic energy	
avoiding disruption and pollution	7. Seas with natural hydro morphological characteristics	

Table 2. High level objectives of the German MSP and MSFD implement	ation.
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The analysis further revealed that operational objectives however hardly exist in practice. Under the MSFD, Germany had to specify GES by means of defining operationalised indicators with specific targets at the member state level. However, these are still not defined for ecosystem components such as demersal fish. In contrast, the only operational objective of the German MSP is the implementation of the development of OWF to generate 25 GW until 2030. This target was recently reduced to 15 GW by 2030 through the implementation of the Renewable Energy Sources Act (EEG) in 2014.

Given that operational objectives between both instruments were lacking, the following thematic overlaps (high level goals) were identified from the literature review as substitute for more specific commonalities:

- 1. Preservation of biological diversity / prevention of declining diversity
- 2. Preservation of ecosystem structure, functions and processes including the sea bed

The main thematic overlap that the MSP and the MSFD share is therefore the conservation of biodiversity which pertains to MSFD descriptor D1 (biodiversity). The second point is very broad and touches on multiple descriptors but the special reference to the sea bed makes it also relevant to descriptor 6 (sea-floor integrity).

4.1 Spatial management measures likely to affect the achievement of high level objectives

As pointed out earlier, the direct and indirect effects of spatial management measures such as the continued OWF development or the future implementation of management plans in Natura 2000 sites on benthic systems and the demersal fish community are highly uncertainties. The question remains to what extend negative effects caused by economic activities such as fishing and OWFs may be offset by positive aspects through conservation measures providing refuge areas for fish and benthic communities from fishing (Gilbert et al. 2015).

Fishing remains one of the greatest pressures in marine ecosystems by changing the composition, size, age and trophic structure of fish and benthic communities and by removing whole functional groups from the system (Costello et al. 2010; Martins et al. 2012; Thrush et al. 2015). In addition, trawling causes indirect effects through alteration of habitat, prey availability and quality for benthic fish (Kaiser et al. 2002; Hiddink et al. 2016).

Natura 2000 sites in Germany will be likely closed or restricted to bottom trawling and could therefore enhance biodiversity and sea-floor integrity (Table 3). Natura 2000 sites were not designated to conserve biodiversity per se; however, ample literature exists on benefits of

MPAs that include increases in biodiversity such as species richness (Gell & Roberts 2003; Goñi et al. 2011). Also, some evidence of "spill-over" into areas beyond the reserve was documented (Halpern et al. 2009). However, not all MPAs are successful, and this was attributed amongst other factors to a lack in compliance of fishermen (Bacheler et al. 2016). Spatial management measures are only as good as the extent to which the regulated sector(s) are complying with it. Quantitative information about fishermen compliance with existing closed areas such as the Plaice Box or OWFs are not available but are a crucial source of information if the success or performance of a management measure should be assessed (Cormier et al. 2017).

Further, controversy about MPAs is nurtured by the loss of fishing grounds and impacts of effort displacement, potentially resulting in reduced sustainability of remaining open areas (Hilborn et al., 2004). Naturally, the same holds true for effort displacement due to OWFs and so, effects outside of closed areas, whether OWF or MPA, are uncertain (Table 3).

Table 3. Expected effects of OWFs and Natura 2000 sites on MSFD descriptors (D) biodiversity (D1) and sea-floor integrity (D6).

Inside closed area		ea Outside closed area	
Biodiversity (D1)	Sea-floor integrity (D6)	Biodiversity (D1)	Sea-floor integrity (D6)
+/-	-	+/0/-	+/0/-
+	+	+/0/-	+/0/-
	Biodiversity (D1) +/- +	Biodiversity (D1) Sea-floor integrity (D6) +/ + +	Biodiversity (D1) Sea-floor integrity (D6) Biodiversity (D1) +/ +/0/- + + +/0/-

+ indicates positive effects; - indicates negative effects; +/- indicates uncertain effects; 0 indicates no effect

Effects of OWFs on demersal fish fauna and its biodiversity have been discussed controversially and could go "both way" (Wilhelmsson 2010; Hammar et al. 2016): Fish abundance and potentially also biodiversity could increase due to refuge from fishing, a more complex habitat and additional food availability on the wind turbines known as "reef effect" (Langhamer 2012). In contrast, the introduction of hard substrate to a soft bottom environment may be disruptive and cause shifts in community composition or the introduction of neo-biota. OWF will affect sea-floor integrity negatively trough construction and scour protection around wind turbines (Gilbert et al. 2015). Generally, effects of OWF on biodiversity are still not well researched or understood (Inger et al. 2009) and studies to date have mainly focussed on the scale of an individual wind farm, comparing indicators inside and outside OWFs. Large scale and cumulative effects with other activities and their impact on biodiversity are less understood (Lindeboom et al. 2015).

In addition, economic activities or management measures are not the only driver of biodiversity or ecosystem health. Habitat and other environmental factors such as the hydrography, salinity and temperature, sediment and sheer stress are among the variables that have been reported to structure fish assemblages in the North Sea (Daan et al. 1990; Ehrich et al. 2009; Diesing et al. 2013). Some of these variables are strongly affected by climate change; warming temperatures have already been observed to alter fish distribution, community composition and biodiversity in the North Sea (Callaway et al. 2002; Dulvy et al. 2008; Brander et al. 2016). For instance, increases in temperature were attributed to have caused a shift in juvenile plaice into deeper waters outside of the Plaice Box (Beare et al. 2013). Climate change will have vast effects on the environment and the performance of any spatial management measure and introduces additional planning uncertainty (Elliott et al. 2015). Fishing was identified as the most important driver in many marine ecosystems, with often non-additive combined effects with environmental drivers (Link et al. 2010).

4.2 Operationalisation of spatially explicit biodiversity indicators

Assessing the effects of fishing on key ecosystem components such as fish biodiversity requires indicators. They are measures to quantify and simplify information and together with carefully chosen thresholds they can be used to assess the achievement of management objectives or to define decision rules for adaptive management strategies to respond to impacts (Stelzenmüller et al. 2013). Indicators are thus the tool where science and management meet and therefore, have to be viable from both perspectives.

In order to choose appropriate indicators, various authors have proposed selection and viability criteria (Piet & Jennings 2005; Rice & Rochet 2005; Belfiore et al. 2006) (Fig. 4). Operational indicators are further described as having well-understood relationships between state and specified anthropogenic pressure(s) with defined targets (Shephard et al. 2015). First and foremost, indicators need to be relevant to management objectives. Based on the thematic overlap between both MSP and MSFD, the clear focus is therefore on indicators of biodiversity. The Convention on Biological Diversity gives a formal definition of biodiversity in its article 2: *"biological diversity means the variability among living organisms from all sources including, inter alia, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species and of ecosystems"*. This very broad and inclusive definition has given rise to potentially hundreds of indicators and it is generally accepted that a whole suite of indicators is necessary in order to assess biodiversity (Farriols et al. 2017).



Fig. 4. Criteria for the selection of operational indicators from a scientific and management perspective; boxes in blue represent criteria that are critical for the derivation of management targets or thresholds to fully operationalise indicators.

The MSFD monitoring programme differentiates between state and pressure indicators to analyse cause-effect pathways between human activities and their influence on the ecosystem. From this, pressure-state relationships should be analysed to derive clear management targets, i.e. the setting of management thresholds or reference points. Such pressure-state analyses are state of the art in Europe (Fock 2011a). Biodiversity indicators therefore have to be sensitive, responsive, specific and tightly linked to a pressure that is managed (Fig. 4). However, this has posed great difficulties in the past due to insufficient mechanistic understanding of biodiversity in relation to human pressures, especially fishing pressure. Studies have reported contradicting results for the Northern and Southern North Sea with regard to long-term temporal trends (e.g. Greenstreet & Hall 1996; Greenstreet et al. 1999; Rogers et al. 1999; Piet & Jennings 2005). However, earlier studies were based on simple correlation only without accounting for habitat effects; therefore inference should be drawn with caution. In addition, indices such as species diversity are inherently dependant on sample size underestimating actual diversity due to different catchabilities of less abundant species (Magurran 1988; Gotelli & Colwell 2001; Gotelli & Chao 2013). Consequently this has contributed to diversity metrics failing the sensitivity criteria for an operational indicator (Greenstreet & Piet 2008, Greenstreet 2008). This is the main reason why community-level indicators have not been included in the MSFD decision document (EC 2010) as suggested indicators under descriptor 1 (D1). Instead, the MSFD advises measuring biological diversity at the species, habitat and ecosystem-level. Member states have struggled with the latter and have mostly omitted ecosystem indicators. This has left the suite of MSFD biodiversity indicators basically focusing at the species and habitat level. This however does not suffice in an EBM context. None of the biodiversity indicators for fish or benthic communities under the German MSFD monitoring programme³ are currently operationalised and assessment methods are still lacking. The timely development of new biodiversity indicators is important since the EC is revising the MSFD decision document. This may lead to the proposal of additional community-level indicators (ICES 2016) which may inspire a rethinking of currently proposed indicators under the German monitoring programme.

The quantification of pressure-state relationships between fishing and the fish community has instigated a lot of research. More recently, interest has focussed on developing biodiversity indicators that look at important biological traits that provide specific functions in the ecosystem. Analyses based on these functional diversity indices have found more conclusive relationships between fish community biodiversity and fishing in some instances (Halpern & Floeter 2008; Cadotte et al. 2011; Wiedmann et al. 2014).

Indicators should further be tightly linked to the managed activity or pressure in time and space. However, indicators as well as most monitoring surveys have been designed to measure changes in time rather than being spatially explicit (Rochet & Trenkel 2003; Fulton et al. 2005; Rice & Rochet 2005; Smith et al. 2011). Under the MSFD, few spatial indicators are suggested such as species distribution or the distribution of human activities, but their spatial quality has not always been tested. Also, mapping biodiversity is not straightforward mostly due to insufficient sampling effort and lack in standardisation of index calculation. This includes the choice over the modelling technique to be used as well as the mapping approach (Greenstreet & Piet 2008; Granger et al. 2015a). While current studies suggest the direct and the indirect approach, these are not empirically well tested (Granger et al. 2015b). According to the selection criteria, indicators should be measurable across the entire management area (Fig. 4). To be useful for a MSP process, data have to be available at a

resolution fine enough for decision making at a small scale (Janßen et al. 2017). The German Autumn Survey of the Exclusive Economic Zone (GASEEZ) has been carried out since 2004. Therefore, long-term temporal changes in spatial patterns cannot be analysed based on this

³ http://mhb.meeresschutz.info/de/monitoring/indikatoren/region/meeresgewaesser-ans.html (retrieved March 2017)

survey; however, it has the best spatial coverage for the German EEZ. This fisheries independent survey provides the biological data for all analyses in this thesis.

4.3 Bayesian Belief Networks to support spatial environmental risk evaluation

Once indicators have been chosen they can be used to assess the risk of implementing planned management measures to achieve defined objectives. Environmental risk assessments (ERAs) (Hope 2006) that link spatially explicit information on the vulnerability of ecosystem components with the occurrence and magnitude of pressures are fundamental for the successful implementation of an ecosystem-based MSP approach (Stelzenmüller et al. 2010a; Fock 2011a; Gimpel et al. 2013). In the light of harmonising MSFD and MSP in the German Bight, spatially explicit ERAs can be aligned to the on-going spatial management process. A risk assessment framework has recently been described in Cormier et al. (2013) which consists of the risk identification, the risk analysis, accounting for both, the probability and the magnitude of the pressure(s), its impacts on ecosystem components and the degree of uncertainty involved, and finally, the risk evaluation. In this last step likely impacts on ecosystem components are evaluated under alternative management measures.

Quantitative risk assessments rely on mathematical models to predict the response of ecosystem components to changing pressures. In application of a risk assessment the probabilities of a pressure occurring and its likely impacts on the environment are evaluated. This requires a measure of uncertainty. Bayesian Belief Networks (BNs or BBNs) have become increasingly popular in environmental risk assessment (McDonald et al. 2015; Stelzenmüller et al. 2015; McDonald et al. 2016). While they originate from engineering and disaster risk assessments, they are now used in a range of different risk assessment and management contexts and are becoming quite popular in environmental modelling (McCann et al. 2006; Uusitalo 2007; Franco et al. 2016). BNs are probabilistic models that display correlative and causal relationships by first setting up a conceptual model (a directed acyclic graph, DAG) representing the best available knowledge about system functioning. The probabilistic relationships between model components (nodes) are then specified by conditional probability tables (CPT). These relationships or so called cause-effect pathways can either be inferred or respectively learned from the correlation inherent in the data, or they can be specified by expert knowledge or based on equations derived from external models. This is a crucial benefit in an EBM setting, where analyses often fail to define pressure-state relationships.

In addition, providing probabilities instead of a single target provides more viable and realistic information in a management setting that is inherently characterised by uncertainty. Using a BN to evaluate risks of future management measures by means of scenarios provides another advantage of providing a range of possible future scenarios to facilitate decision making in the face of uncertainty. A BN does not follow a prescribed model structure and there are hardly any constraints in the model set up other than not allowing for feedback loops. This makes BNs extremely flexible and provides the opportunity to represent all important components and links that characterise the system under study. BNs are capable of combining qualitative and quantitative data. Opportunities, risks and uncertainty can be made explicit by providing probability distributions for each model component. In addition, different spatial and temporal scales can be represented in one model (Wooldridge et al. 2005). This is another important aspect because environmental responses and changes to OWFs and resulting relocation of fishing effort will likely differ at varying spatial scales. Given that in an EB-MSM setting scenario information and predictions need to be spatially explicit, BNs have to be set to accommodate spatial data. Several options have been proposed such as modelling spatial dynamics separately and including results into BN nodes (Grêt-Regamey et al. 2013), implicitly by representing each sub-set of the study area by a node (Chrastansky & Callies 2011), or by fully integrating with a geographic information system (GIS) (Stelzenmüller et al. 2010b; Verweij et al. 2014; Liu et al. 2016).

5. Thesis objectives

The aim of this thesis is thus to help operationalise EB-MSM by providing spatially explicit information on key ecosystem components that allow assessing risks and trade-offs of spatial management measures on demersal fish biodiversity and benthic communities to support decision making. Specifically, it is tested if spatially resolved indicators relevant to MSFD implementation can support spatial management and planning processes in safeguarding marine biodiversity. The achievement of multiple management objectives and targets through current and future management is evaluated. This led to the following three research questions:

- 1. How can community-level biodiversity indicators best be represented spatially to provide information in an EB-MSM context?
- 2. Can a community-level biodiversity indicator be operationalised to link spatial changes in biodiversity state to fishing pressure?
- 3. What are the likely risks of integrating Blue Growth and conservation objectives for the biodiversity of fish and benthic communities in the German Bight?

In this thesis i) different mapping approaches are compared to spatially represent established and newly developed biodiversity indicators at the community-level based on the distribution of demersal finfish abundances across German North Sea waters (Chapter 2); ii) the quality of a novel trait-based indicator to describe spatial pressure-state relationships with fishing pressure from three bottom trawl fleets is tested to inform spatial management as part of a MSP process (Chapter 3), and iii) the risks of future spatial management measures such as the redistribution of fishing effort due to OWFs on benthic communities are simulated (Chapter 4), as well as risks of all management measures (OWF, Plaice Box and Natura 2000) on demersal fish biodiversity under consideration of compliance and climate change (Chapter 5). Chapter 6 finally discusses results of addressing the three research questions and what this entails for the practical alignment of linking Blue Growth with conservation objectives. Remaining research gaps as well as future needs are presented to operationalise EB-MSM from a scientific and management perspective.

The Challenges:

- 1. Integrating Blue Growth with conservation to achieve sustainable use of marine resources
- 2. Ecosystem-Based Marine Spatial Management to facilitate integration is not operational
- 3. Lack in integrated assessments to test spatial effects of economic activities on marine ecosystems

The main question:

How can we provide spatially explicit information to evaluate risks of spatial management measures on fish biodiversity and vulnerability of benthic communities in the German Bight?



Box. 2 Graphical representation of the thematic outline and justification of the thesis including data and analysis methods, the study area featuring the main components analysed as well as the main policy instruments and finally topics presented in each chapter (CFP: Common Fisheries Policy; HD: Habitats Directive; MSP: Maritime Spatial Planning (Directive); MSFD: Marine Strategy Framework Directive, GASEEZ: German Autumn Survey of the Exclusive Economic Zone; VMS: Vessel Monitoring System; SAR: Swept Area Ratio; STB: Sea Bottom Temperature, OWF: Offshore Wind Farm; BN: Bayesian Belief Network; GIS: Geographical Information System).

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Chapter 2

Mapping fish community biodiversity for European marine policy requirements

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Abstract

Predictive maps of biodiversity patterns are pivotal to marine conservation and marine spatial planning alike, yet mapping of biodiversity indicators at the community-level is neither straightforward nor well-tested empirically. Two principle approaches exist. A direct approach involves calculation of indices for each sample, followed by interpolation to estimate values at unsampled locations. An indirect approach first interpolates individual species distributions and then determines indices based on the stacked distribution maps. We compared the appropriateness of both approaches to provide management-relevant information by mapping the distribution of demersal fish biodiversity in the German North Sea EEZ using species richness, Hill's N1 and a novel traits-based community sensitivity to fishing index (CSI). To substitute zero-inflated species with up to 95% zeros in the sample data, we applied each species' mean abundance value as a flat surface. Spatial patterns between indicators varied, but certain hot- and cold-spots were revealed, which, under current legislation, might suggest that the present level of biodiversity protection is insufficient. Despite both approaches generating similar main patterns, the direct approach predicted a narrower range of index values and only depicted the most dominant patterns. Contrary to that the indirect approach better reproduced the variability in the data, along with additional information on species distributions and a theoretical advantage pertaining to sampling issues. While the choice over the mapping approach is context dependent, for our study area featuring a community with relatively few species, we consider the indirect approach to provide the more reliable information for implementing marine environmental legislation.

Keywords: biodiversity mapping, spatial statistics, species diversity, species distribution, community sensitivity index, demersal fish community, MSFD, biodiversity hot-spots

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1. Introduction

Conservation of marine biodiversity has become a high-level policy objective since the Convention of Biological Diversity in 1992. In Europe, the main drivers are the Marine Strategy Framework Directive (MSFD) (EC, 2008) and the Habitats Directive (EC, 1992). The MSFD promotes healthy ecosystems and requires "good environmental status" to be achieved by 2020. The Habitats Directive requires a network of (marine) reserves be established to safeguard specified species and habitats that are at risk. These Directives require biodiversity conservation goals to be aligned with social and economic objectives, which are regulated through the Common Fisheries Policy (CFP) and the newly implemented Maritime Spatial Planning (MSP) Directive (EC, 2014). The latter requires Member States to devise maritime spatial plans through till 2021. However, policies in both areas have developed separately from each other and weak links between European marine legislation along with a lack of clarity regarding the meaning of sustainability, have left the current policy landscape fragmented (Salomon and Dross, 2013; Qiu and Jones, 2013b; Rice, 2011). This is exacerbated by the fact that biodiversity science has not been fully integrated into fisheries research (Thrush et al., 2015), with the result that a functional theory of fish community biodiversity has not been properly developed (Greenstreet, 2008).

Predictive maps are an essential tool in conservation and MSP to assess the state of biodiversity spatially across marine areas that are increasingly exploited. Yet, despite the seemingly limitless number of potential biodiversity indices and interpolation or modelling techniques, our understanding of how to map biodiversity is still limited (Di Battista et al., 2016; Ferrier, 2002; Guisan and Zimmermann, 2000). Biodiversity is scale-dependent (Chase and Leibold, 2002) and diversity measures are affected by variation in and magnitude of sampling effort (Chao et al., 2014). Consequently, mapping of demersal fish biodiversity indicators across the North Sea has only been achieved by using aggregated sample data from large-scale surveys (e.g. Fraser et al., 2008; Greenstreet and Piet, 2008). However, to inform marine spatial planning and conservation at national levels, indicator maps at fine spatial scales are required, and in these circumstances, a similar sample aggregation approach would not be appropriate. While different measures have been proposed to address issues with sampling effort (Gotelli and Colwell, 2001), or how to partition regional-scale diversity into alpha- (local) and beta- (among sites) diversity components (Legendre et al., 2005; Jost et al., 2010), these are neither standardised or routinely used to compare biodiversity data. Furthermore, catchability of fish species is gear-dependent (Fraser et al., 2008) and rare species are frequently not representatively sampled by standard surveys, therefore leading to

potentially unreliable indices, particularly the underestimation of species richness. Generally, comparative studies of spatial biodiversity patterns have focused on the different predictive modelling techniques rather than empirically testing different mapping approaches (Ferrier and Guisan, 2006).

The two most common approaches involve the direct or indirect mapping of biodiversity indicators. With the direct approach, also known as "assemble first, predict later", an index value is calculated from the species abundance data collected at each individual sampling station. The resulting indices are then modelled to estimate equivalent index values at locations that have not been sampled (Ferrier, 2002; Ferrier and Guisan, 2006; Mokany et al., 2011; Smoliński and Radtke, 2016). With the indirect approach ("predict first, assemble later"), individual species distributions are modelled first based on sample species abundance or presence/absence data. The ecological index is then calculated at each grid node from these gridded species distribution data (Lehmann et al., 2002a; Overton et al., 2002; Ferrier and Guisan, 2006). The direct approach is attractive because of its simplicity and speed of calculation. It includes all species in each sample and uncertainty at each point in space is a direct output from the modelling procedure. However, indicators may show weak autocorrelation making geostatistical methods not feasible or be only weakly related to environmental variables. This approach makes the somewhat unrealistic assumption that all species aggregate in the same way by uniformly responding to the environment and/or are sampled equally representatively (Franklin, 1995). As previously mentioned most surveys lack the sampling effort to detect all species present. Therefore, interpolating indices derived from observed species data incorporate this sampling artefact and lead to underestimation of index values (Gotelli and Chao, 2013).

The indirect approach potentially offers more flexibility by modelling species separately and thus better captures individual species responses. Species distribution maps can generally be combined from various surveys and these offer additional species-level information that complements the community-level indicator maps. The main drawback of this approach is that it is difficult to include zero-inflated species that cannot be adequately spatially modelled because of the excessive fraction of zero values in the sample data (Morfin et al., 2012). Zero-inflation encompasses both types of zeros, those that represent real absence of a species and those "false" zeros that have been caused by imperfect detection, sampling or observer error (Martin et al., 2005). While nowadays new powerful models are implemented that can deal with both kinds of zeros (Iknayan et al., 2014; Wenger and Freeman, 2008), the latter are

rarely addressed in community-level biodiversity studies. Models that allow for a certain level of excess zeros are amongst others hurdle models, delta models, Bayesian models, machine learning methods and zero-inflated Poisson generalized models (Agarwal et al., 2002; Escalle et al., 2016; Quiroz et al., 2015; Barry and Welsh, 2002; Welsh et al., 1996). However, there is always a limit to the level of zero-inflation that can be handled. Rare species are often of greatest conservation concern and because these species generally have the most zero-inflated distributions, the practicality of the indirect approach in this respect has been questioned (Ferrier and Guisan, 2006). In addition, this approach is more time-consuming, and the display of uncertainty is not so straightforward.

The precise nature of the relationship between changes in fish community biodiversity indices and variation in fishing disturbance has not been clearly established, which explains why such indicators are not included in current European biodiversity monitoring programmes in support of the MSFD (Greenstreet, 2008). We therefore constructed the community sensitivity to fishing index (CSI) specifically to address this shortcoming. The CSI is based on four livehistory traits namely ultimate body length, growth rate and age- and length-at-first-maturity, which have been used to characterise a species' sensitivity to additional mortality from fishing pressure (Greenstreet et al., 2012; Le Quesne and Jennings, 2012; Jennings et al., 1999). Thus, mapping areas of higher fish sensitivity to fishing may help to address the challenge of integrating fisheries management with biodiversity conservation objectives. Species richness remains a dominant concept in policy advice and planning despite a multitude of studies questioning this concept (Gotelli and Colwell, 2001). Hence, in addition to the newly developed CSI, we also mapped two traditional taxonomic indices, the Hill numbers N₀ (species richness) and N₁ (the exponential of Shannon's entropy index) to display different aspects of biodiversity and sensitivity to fishing.

Few studies comparing different approaches to mapping biodiversity indicators exist (Granger et al., 2015; Ferrier and Guisan, 2006) and none included mapped outputs in their discussion. In this study we address this gap using two principle approaches, both utilising ordinary kriging (Cressie, 1988), to map fish community biodiversity. We consider both approaches to assess which is the most appropriate applied to three different ecological indicators. Further, we discuss drawbacks and advantages of both approaches and suggest potential improvements. Finally, we discuss the scientific and policy implications of the resultant maps of each indicator in respect of the demersal finfish community in and around the German Exclusive Economic Zone (EEZ) of the North Sea.

2. Material & methods

2.1 Data source and preparatory analysis

We conducted our study in the German EEZ of the North Sea and coastal adjacent waters (see Fig. 1). To produce fine scale resolution maps necessary to support the German MSP process, we used data from the German Autumn Survey for the EEZ (GASEEZ). The primary objective of this monitoring programme is to assess spatial and temporal changes in local fish communities associated with human exploitation (Neumann et al., 2013). The GASEEZ has the best spatial coverage across the German EEZ of the North Sea and so provides appropriate data for mapping demersal fish biodiversity. GASEEZ sampling has been conducted annually in late autumn since 2004 sampling a maximum 75 fixed stations using otter and beam trawl gears in alternate years.



Fig. 1. German EEZ of the North Sea with depth profile, fixed sampling stations of the GASEEZ survey used in this study and a description of its ecosystem provinces based on Rachor and Nehmer (2003), A: Eastern German Bight, B: Inner German Bight, C: South-western German Bight, D: Northwestern German Bight, E: Elbe River Glacial Valley, F: Transition zone between German Bight and Dogger Bank, G: Dogger Bank, H: Central North Sea.

For our comparative analysis we used catch per unit effort (CPUE) data collected by the beam trawl (7 m beam, 20 mm codend) to avoid the issue of different catchability between the two gears. We considered just the years 2005, 2009 and 2013, in which the majority of stations were sampled. We then combined the data from these three years to derive a single aggregated data set with sufficient sample sizes to support the spatial analyses and to reduce the level of zero-inflation in the data (Stelzenmüller et al., 2006). Pelagic species, considered to be inadequately and non-representatively sampled in the beam trawl gear, were excluded

from the analysis leaving a dataset that comprised CPUE data for a suite of 48 demersal species caught in a total of 189 hauls (Table 1). We standardised CPUE data to 15 min trawling; trawl speed, and hence the distance trawled per unit time trawl distance was similar between hauls, so CPUE data reasonably reflects fish density at each trawl sample location. To map these data, the trawl mid-point positions were used which varied between years. Finally, the trawl CPUE data were interpolated to a 5 by 5 km grid across the study area.

2.2 Biodiversity indicators and the community sensitivity index

The complex definition of biodiversity has given rise to a large variety of different indices, each of which generally captures different aspects of biodiversity. Consequently, no single index has thus far been universally accepted (Di Battista et al., 2016). Most studies of biodiversity therefore apply a suite of indicators; we also adopt this approach. We used Hill's (1973) N₀ to monitor spatial variation in species richness (S, defined as the number of species/taxonomic groups) and N₁ (the exponent of the Shannon's entropy index) as a measure of the "effective number of species" (Jost, 2006). To some extent, N₁ combines elements of both species richness and species evenness, but is strongly influenced by variation in the latter. The index is derived by N₁ = $\exp[-\sum_{i=1}^{S}(p_i \ln p_i)]$, where p_i is the proportion of species i and S is the number of species.

Additionally, based on the approach described by Greenstreet et al. (2012), we developed a community sensitivity to fishing index (CSI) to derive an ecological indicator that can identify fish communities with a species composition that would render them particularly sensitive to increases in fishing pressure. The CSI uses species' life history traits such as length, growth and maturity, which represent functional aspects of biodiversity. Metrics that incorporate life history variability have recently been found to complement traditional metrics of species diversity (Stuart-Smith et al., 2013) and may offer greater explanatory power than traditional taxonomic-based indicators (Cadotte et al., 2011). Greenstreet et al. (2012) calculated SIs for 119 North Sea finfish species. SIs are derived from the arithmetic mean of four standardised life history trait variables: ultimate body length, the growth parameter k, and length- and age-at-first-maturity. These traits are closely linked with a species' capacity to cope with mortality rates above those normally experienced under natural environmental conditions e.g. caused through fishing (Jennings et al., 1999; Jennings et al., 1998; Le Quesne and Jennings, 2012).

Scientific name	Species name	% zero	Total	SI
Limondo limondo	Dob	catches	22.070	0.179
Disurgenestes platasse	Dao	0	55.070	0.178
Arnogloggue laterne	Maditarrangen soglafish	2 10	0.558	0.290
Amogiossus laterna		10	4.003	0.073
Agonus cataphractus	Draganat	14	4.830	0.129
Camonymus tyra Marlangius marlangus	Whiting	20	1.974	0.123
Duele asi dina lutana	vy mung S a lan atta	22	073	0.170
Bugiossiaium luteum	Soleneue Sand sake	24	14.029	0.131
Pomatoschistus minutus	Sand goby	21	10.495	0.049
Gadus mornua	Atlantic Cod	40	290	0.333
Myoxocephalus scorpius	Shorthorn sculpin	49	613	0.187
Microstomus kitt	Lemon sole	53	686	0.235
Solea vulgaris	Common sole	55	323	0.217
Syngnathus rostellatus	Nilsson's pipefish	59	591	0.095
Eutrigia gurnardus	Grey gurnard	59	411	0.248
Liparis liparis	Striped seasnail	68	694	0.090
Rhinonemus cimbrius	Fourbeard rockling	74	178	0.224
Platichthys flesus	Flounder	75	126	0.246
Callionymus reticulatus	Reticulated dragonet	79	198	0.064
Ciliata mustela	Fivebeard rockling	79	142	0.111
Hippoglossoides platessoides	American plaice	83	248	0.177
Hyperoplus lanceolatus*	Great sandeel	85	41	0.177
Trigla lucerna	Tub gurnard	85	47	0.331
Raja radiata	Starry ray	86	242	0.31
Ammodytes marinus*	Lesser sandeel	89	28	0.136
Echiichthys vipera	Lesser weever	92	43	0.09
Scophthalmus rhombus	Brill	93	14	0.289
Entelurus aequoreus	Snake pipefish	94	12	0.268
Psetta maxima	Turbot	94	11	0.298
Mullus surmuletus	Surmullet	95	27	0.164
Melanogrammus aeglefinus	Haddock	95	11	0.273
Gasterosteus aculeatus*	Three-spined stickleback	96	14	0.065
Ammodytes tobianus*	Small sandeel	96	15	0.085
Trisopterus luscus	Pouting	96	7	0.165
Phrynorhombus norvegicus	Norwegian topknot	98	4	0.072
Raniceps raninus	Tadpole fish	98	4	0.156
Diplecogaster bimaculata	Two-spotted clingfish	99	3	0.024
Spinachia spinachia	Sea stickleback	99	1	0.058
Argentina sphyraena*	Argentine	99	1	0.128
Taurulus bubalis	Longspined bullhead	99	1	0.176
Lampetra fluviatilis	European River Lamprey	99	2	0.238
Glyptocephalus cynoglossus	Witch flounder	99	1	0.254
Zeus faber*	John dory	99	1	0.283
Cyclopterus lumpus	Lumpfish	99	1	0.322
Zoarces viviparus	Ealpout	99	1	0.332
Scyliorhinus canicula	Lesser spotted dogfish	99	1	0.367
Lophius piscatorius	Angler	99	1	0.415
Raja montagui	Spotted ray	99	1	0.416
Molva molva	Common ling	99	2	0.482

Table 1. All 48 species considered in the analysis, the percentage of how often they weren't caught in all hauls, their total CPUE and their species specific sensitivity indices (SI).

* SIs were calculated based on provided formulae in Greenstreet et al. 2012

For most species sampled in the GASEEZ we simply used the SI established by Greenstreet et al. (2012); for species not included in Greenstreet et al. (2012), we calculated the index using the formulae provided (Table 1) applied to data obtained from the FishBase website (www.fishbase.org). The CSI is computed as a sum of species SIs, weighted by the individual species' CPUE, and standardised by the total number of individuals caught:

$$CSI = \frac{\sum_{i=1}^{n} n_i SI_i}{N},$$
(I)

where n_i is the number of individuals of species i, N is the total number of individuals and SI_i is the SI of species i. A similar approach has been used by Schmiing et al. (2014) based on global values of fish vulnerability (Cheung et al., 2005). Individual species' SIs have been classified into three categories: resilient (0.011 – 0.164), intermediate (0.165 – 0.31) and sensitive (0.311 – 1) simply on the basis of the 33 percentiles of all 119 species' SIs (Greenstreet et al., 2012). A similar logic could be applied to the CSI. Other life-history based metrics exist for fish communities such as resilience to fishing pressure (Musick, 1999) published on FishBase that uses slightly different input parameters than the CSI. However, only one of the parameters suffices to produce the metric and estimation methods are not always clear (www.fishbase.org). In addition, the CSI is specifically tailored to the North Sea fish community and thus better represents the community in the study area.

2.3 Spatial modelling

Many comparative studies on spatial modelling and interpolation techniques have been published. While results suggest that the choice over the appropriate method is most often context dependent, generalized additive or linear models that employ (a)biotic variables to account for spatial heterogeneity have received a lot of attention in the past (Lehmann et al., 2002b). In the German Bight, environmental variables such as temperature, salinity, sediment and depth have been reported to influence the distribution of species (Stelzenmüller et al., 2005). Initial tests with directly mapping S and N_1 by means of a generalized additive model (GAM) with the aforementioned variables did however account for less than a fourth of deviance explained. We therefore used ordinary kriging, a standard geostatistical interpolation method (Petitgas, 2001; Li and Heap, 2011) to predict the distribution of species' CPUE as well as indicators under the direct mapping approach.

Kriging describes the strength and nature of spatial autocorrelation, e.g. the shape and size of the patches in which a species aggregates. To analyse this spatial structure, we calculated omnidirectional and unidirectional (0-135°) experimental semivariogrammes based on the robust modulus estimator (Cressie, 1991). Since linear relationships with temperature, salinity

and depth were weak, we used 2nd order polynomials for most semivariogrammes to remove any spatial trend. We then fitted the model parameters, nugget (y-axis interception point), partial sill (difference between the maximum level of variation found in the data and the nugget value) and range (distance from each sample point where there is no more autocorrelation), based on weighted least squares (Cressie, 1991). We employed a 'leave-oneout' cross-validation procedure to evaluate the appropriateness of the model (Isaaks and Srivastava, 1989). A good representation of the data can be assumed if the cross-validation between the observed and the predicted values produces a mean of the standardised error (Zscore) around 0 and a standard deviation (SD Z-score) around 1. For final model selection we used the goodness of fit procedure recommended by Fernandes and Rivoirard (1999) where the value should be as close to zero as possible. We then used the selected model to interpolate each grid node value. Analyses were conducted in the statistical language R version 3.0.3 (geoR package for geostatistical analysis) and ArcGIS 10.1.

2.4 Direct and indirect mapping

We applied both a direct and an indirect approach for mapping all three ecological indicators (Granger et al., 2015). For the direct approach we calculated all indices using the sample species CPUE data, followed by an interpolation to estimate equivalent indicator values for all grid nodes across the study area. For the indirect approach we first interpolated the individual species CPUE data obtained at each sample location, and then calculated each ecological indicator value at each grid node using the interpolated species CPUE data. Both approaches eventually produced estimates of each ecological indicator at all grid nodes. The major drawback of the indirect approach is that only species whose distributions can be interpolated can be included. In our study, this was the case for just 19 of the 48 species (refer to Supporting information, Appendix S1 for individual species distribution maps of these 19 species). These species were caught in at least 20% of sampling stations (Table 1). Since there is no specific protocol for defining the degree of zero-inflation that still permits reliable interpolation, any limits set are arbitrary and must ultimately depend on the data and survey design.

To increase the number of species being included in the indirect approach, we applied a 'mean value approach' to species that, although rarely encountered, were sampled at random locations across the whole study area. The logic underlying this is that these species were too data-deficient for the kriging analysis to detect significant spatial structure in their CPUE data. When a (semi)variogramme analysis suggests a lack of spatial structure, the most appropriate surface to fit to the data is equal to the mean of all the values (ICES, 2015).

Given that the nugget of a spatial model is the equivalent to the intercept in a linear regression model, the mean value approach is essentially the equivalent to the use of the mean Y value when the slope is not significantly different from zero (mean Y equals the intercept with b=0). The null hypothesis of 'no spatial structure' was therefore applied and the mean CPUE determined across all samples for each species was simply assigned to each grid node. We applied this approach to each species separately after careful consideration of sampling occurrence and used expert knowledge on respective habitat preferences. For some species too data-deficient to support kriging, it was clear that they were only ever observed within a restricted part of the study area. In these cases, only the samples from this restricted area were used to derive a mean CPUE estimate within this region (Table 2); all other grid nodes were set to zero. Applying this approach to species where 80-95% of the CPUE values were zero allowed us to include a further 11 species, bringing the total number of species to which the indirect mapping approach could be applied up to 30. We excluded all other species observed in less than 5% of samples (Morfin et al., 2012); in fact the majority of these species were actually encountered only once in the data set (Table 1). However, since it is argued that very rare species are often particularly sensitive to human pressures, we mapped their presence in our sampling data to complement the indicator maps (Supporting information, Appendix S2). Actually only a third of these species were classified as being sensitive to additional fishing pressure based on the classification of Greenstreet et al. (2012).

Non-normal distribution data can severely influence kriging results, so all CPUE data were log-transformed with a constant of 1 added to facilitate log-transformation of zero observation. The interpolated CPUE values were back-transformed and the previously added constant of 1 subtracted before calculating the ecological index values at each grid node (McDonald, 2014).

In the direct approach we initially calculated each ecological indicator using the CPUE data for all species sampled at each station. The resulting interpolated indicator values were therefore based on the full suite of 48 species contained within the data set. To test the effects of excluding the rarely encountered species, we additionally computed each ecological indicator using only the subset of 30 species that could be analysed in the indirect approach. Results suggested no significant difference between maps (see results section). Generally a methodological comparison between mapping approaches would be performed on the same species list. **Table 2.** Estimated parameters (nugget, partial sill, and fitted range) of models fitted to the averaged semivariogramme of each species and directly mapped indices (CSI, species richness, N1) and the goodness of how models represent the data described by the GOF value, the mean (mean Z-score) and standardized error (SD Z-score) of the cross-validation procedure.

	Model	Nugget	Partial	Fitted	Spatial		Mean Z gooro	SD
Species name				range	depen-	GOF		SD Z seere
			5111	[°]	dency		Z-score	Z-score
Dab	gaussian	0.5	1.4	1.7	0.36	0.0011	0.0002	1.51
Plaice ^a	spherical	0.68	0.38	1	1.79	0.0005	-0.0019	1.005
Med. scaldfish	spherical	0.9	0.55	1	1.64	0.0003	0.002	1.013
Hooknose	spherical	0.95	0.7	1.2	1.36	0.0002	0.0019	1.07
Dragonet	spherical	0.6	0.7	0.6	0.86	0.0013	-0.0014	1.02
Whiting	nugget	0.54	-	-	n.a.	0.0062	n.a.	n.a.
Solenette ^a	spherical	0.2	4	0.6	0.05	0.0065	0.0068	1.009
Sand goby	spherical	0.56	1.2	0.6	0.47	0.0014	-0.003	1.58
Atlantic cod	gaussian	0.25	0.18	0.6	1.38	0.0059	-0.0036	1.15
Shorthorn sculpin ^a	spherical	0.16	0.5	1.8	0.32	0.0007	0.0003	2.59
Lemon sole	nugget	0.5	-	-	n.a.	0.3643	0.0005	1.03
Common sole	spherical	0.18	0.42	0.6	0.43	0.0017	-0.0041	2.15
Grey gurnard ^b	gaussian	0.05	0.4	1	0.13	0.0051	0.01	5.5
Nilsson's pipefish	spherical	0.2	0.4	1	0.50	0.0019	0.0027	4.8
Striped seasnail	spherical	0.1	0.45	1	0.22	0.0007	0.0012	2.2
Fourbeard rockling	exp.	0.2	0.38	1.5	0.53	0.4789	0.0025	1.04
Flounder	spherical	0.04	0.16	1.5	0.25	0.0001	-0.0008	3.55
Reticulated dragonet	spherical	0.01	0.25	1.2	0.04	0.0011	-0.01	16.77
Fivebeard rockling	spherical	0.04	0.2	1.6	0.20	0.0015	-0.0005	4.15
American plaice	mean distr	-	-	-	-	-	-	-
Tub gurnard	mean	-	-	-	-	-	-	-
Great sandeel	mean distr	-	-	-	-	-	-	-
Starry ray	mean distr	-	-	-	-	-	-	-
Lesser sandeel	mean	-	-	-	-	-	-	-
Lesser weever	mean	-	-	-	-	-	-	-
Brill	mean distr	-	-	-	-	-	-	-
Snake pipefish	mean	-	-	-	-	-	-	-
Turbot	mean	-	-	-	-	-	-	-
Haddock	mean distr	-	-	-	-	-	-	-
Surmullet	mean	-	-	-	-	-	-	-
Species richness	spherical	3.5	2.2	0.9	1.59	0.0006	-0.0006	1.05
Hill's N ₁ ^b	gaussian	1.4	0.9	0.8	1.56	0.0012	0.0003	1.11
CSI	spherical	0.0003	0.0002	0.8	1.65	0.0052	-0.0001	1.21

mean= mean value applied to all grid cells; mean distr= mean value applied only to distribution range, other grid cells set to zero; exp.= exponential; ^amodelled without 2nd order polynomial; ^bmodelled with a unidirectional semivariogramme

However, given the similarity between map outputs and that in a situation where the direct mapping approach was actually being used to provide scientific advice to support management policy, this advice would invariably be based on analysis of all the data available. In the subsequent analysis we therefore only considered results for directly mapped ecological indicators that were based on data for all species.

We used mantel tests with spearman rank correlation and 1000 permutations (Mantel, 1967) to evaluate the degree of correlation between directly and indirectly derived maps. Mantel tests are regression techniques that convert variables into distance matrices summarising pairwise similarities among sample locations. This provides estimates of the degree of correlation between the variables. We used Euclidian distance to derive the matrices and a 5% probability to define significantly correlated distributions. To assess the fit of predicted versus observed values, we extracted indirectly and directly predicted grid node values at the sampling locations and fitted linear models to the data. We then tested the significance of the relationships against the null-hypothesis of slope=1 and intercept=0. Additionally, we compared both approaches by ANCOVA, i.e. the slopes and intercepts from the linear models describing the relationship between the observed and predicted values were analysed for statistically significant differences.

Quantifying model uncertainty is particularly essential in any decision making process. For the direct approach, mapping of kriging errors (the standard deviation of the kriging variance) shows where predictions vary from the observed value and by how much. For the indirect approach this is not straightforward (Guisan et al., 2006). Essentially, error propagation needs to be assessed (Heuvelink and Burrough, 2002). However, this is difficult to depict because the total variance would be at the scale of the CPUE estimates and not the ecological index. Hence, we used the kriging errors (standard deviations) from the species predictions and first added and then subtracted these values from the CPUE prediction values. For the mean values of the 11 "rare" species which we substituted using the mean value approach (see above), we calculated respective standard deviations. We eventually recalculated the upper and lower bound of all indices based on the maximum and minimum predicted species CPUE. For the direct approach we added and subtracted the kriging errors from the indices to derive the upper and lower index bounds.

The main strengths and weaknesses of both approaches were considered using Strength-Weakness-Opportunities-Threat (SWOT) analysis. A SWOT analysis visualises and combines the strengths and weaknesses in any situation or approach along with opportunities and related threats to develop strategies to reach a predefined target (Weihrich, 1982).

2.5 Indicator assessment

To assess whether the three ecological indicators revealed similar spatial patterns of high and low biodiversity, a hot-spot analysis was conducted using the ArcGIS spatial statistics toolbox based on the Gertis-Ord-Gi* statistic (Zhang, 2008). We chose Euclidian distance with a fixed distance of 5 km to visualise hot- and cold-spots for all three indicators and compared each indicator pair. Hot- and cold-spots were defined as grid nodes with values higher or lower than -1.96 standard deviations from the mean. Areas of overlap across indicators (areas where all or at least two indicator combinations shared hot- or low-spots) were identified and compared with other activities in the EEZ. Specifically, we overlaid the map output with current priority areas for offshore wind farms (OWF) under the German maritime spatial plan (BSH 2016, status January 2016) as well as Special Areas of Conservation (Natura 2000 sites) as currently defined under the Habitats Directive.

Wide-spread, abundant species are frequently more influential on spatial ecological indicator values. An assessment of each indicator's sensitivity to individual species distributions is therefore important in any overall evaluation of the robustness of a modelled index (Stelzenmüller et al., 2010a). Here, we tested the sensitivity of N_1 and the CSI based on the indirect maps only, by excluding species in turn, recalculating the N_1 and CSI maps, and determining the proportion of grid cells with altered index values. Naturally, for species richness a similar analysis would be meaningless, since abundance is not considered in the calculation of S.

3. Results

3.1 Structural analysis of spatial models

With the exceptions of lemon sole and fourbeard rockling, interpolated individual species distributions and ecological indicator distributions closely fitted (GOF values <0.01) the observed sample data; a conclusion further corroborated by the low mean Z-Scores obtained in the cross-validation procedure (Table 2). However, as the degree of zero-inflation in individual species CPUE data increased, so also did the Z-score SD. The majority of species were best represented by spherical models. Structural analysis of semivariogrammes revealed that spatial aggregation patterns were generally stronger (the slope of the semivariogrammes steeper) in individual species CPUE models than for any of the directly modelled indices. This was confirmed by higher spatial dependency of individual species (Table 2). The strength of spatial dependency can be derived from the semivariogramme expressed as the

ratio of nugget and sill; the lower the ratio, the higher the autocorrelation or spatial aggregation pattern. In contrast, spatial dependency was low for the directly modelled indices.

3.2 Comparison of mapping approaches

Significant spatial overlap was detected between each indicator modelled by the direct and indirect approach. However, Mantel test correlations between maps was low for the two diversity indices, S (r = 0.3211, P = 0.001) and N₁ (r = 0.4007, P < 0.0001), but maps of the CSI derived by both methods were more closely correlated (r = 0.765, P = 0.001) (Fig. 2). This was confirmed by ANCOVA results: the interaction term was significant for S (P < 0.01) and N₁ (P < 0.05) models, meaning that slopes and therefore intercepts between both approaches were significantly different. This was however not the case for the CSI (P > 0.1). The comparison of the directly modelled maps based on all 48 (Fig. 2, upper row) and 30 species only (Fig.2 middle row) were surprisingly identical for N₁ and CSI. Whether based on all species or just the subset, the same models best described the spatial structure of these indices. Final maps of S based on all 48 or just 30 species showed minimal differences, only. Although both approaches generated generally similar main patterns in the three ecological indicators, the key observation was that the indirectly modelled maps seemed to better describe the variability in the data by displaying a greater level of detail.

This was also the case for the CSI predictions, despite similar slopes between both methods. The directly modelled maps lacked this higher spatial variability, only revealing the principal underlying patterns (Fig. 2). This observation was confirmed by a narrower range of directly mapped predictions, while the indirectly mapped predictions better displayed local minima for the CSI and maxima for N₁. Observed values for N₁ actually ranged from 1.8 - 9.6 across all grid nodes, while modelled values ranged between 2.5 and 8.5 using the indirect mapping method; this range was even further reduced to between 2.8 and 6.3 using the direct mapping method. Similarly, observed values of the CSI ranged between 0.064 and 0.216, between 0.085 and 0.212 when modelled using the indirect method and between 0.105 and 0.21 when using the direct method. Species richness observed in the samples ranged from 8 to 17 species, similar to the actual sample data range, which was to be expected. What was perhaps less expected, particularly given that 18 of the 48 species analysed using the direct method could not even be included in the indirect analysis, was the range in species richness of 20 to 27 species.



Fig. 2. Spatial distribution of species richness (S), Hill's N_1 and the community sensitivity index (CSI) [from left to right]; distribution maps were modelled using the direct approach based on all 48 species [upper row] and on 30 species only [middle row] as well as the indirect approach based on 30 species [lower row].

In both approaches there was therefore a tendency for modelled estimates to exceed observed data towards the lower end of these ranges, and vice versa towards the upper end of these ranges as indicated by all slopes of regression lines being less than 1 (Fig. 3).

In fact statistical analysis showed that slopes and intercepts between observed values and predictions of all indicators significantly differed (P < 0.0001) in both approaches. Regression statistics were also generally weak to intermediately strong and ranged between observed and directly mapped indices from $r^2 = 0.433$ to $r^2 = 0.595$ and from $r^2 = 0.332$ to $r^2 = 0.578$ for indirectly mapped indices (Fig. 3).



Fig. 3. Comparison of observed versus predicted indicator values (species richness, Hill's N_1 and the CSI) estimated by the direct (in blue) and the indirect (in green) mapping approach; the bisector symbolises a perfect prediction of observed values where x = y.

Uncertainty of model prediction, displayed as the range between the upper and lower bounds of each index, was overall lower in the indirectly calculated indices for the CSI, similar for N_1 and higher for S when compared with the direct approach (Fig. 4). Overall, indicator patterns did not change between the upper and lower bounds of predictions which was to be expected for the direct approach since the kriging error is symmetrical. This was however also the case for the indirect predictions with the exception of the upper bound of S. For indirectly mapped S, there was a considerable difference between the upper and lower prediction bounds. The upper bound predicted more species to occur in the northern part of the EEZ but otherwise being very similar to predicted values (Fig. 2), while the lower bound predicted up to 18 species less to occur. However, the pattern and range of lower bound predictions (6 to 17 species) were very close to observed values.



Fig. 4. Uncertainty range represented by the upper and lower index bounds based on recalculation of indices with upper and lower predictions. This was derived by adding and subtracting kriging errors from the index predictions (direct approach) and the species predictions (indirect approach), respectively.

3.3 Comparison of biodiversity indicators

Figure 2 does not immediately suggest any coherent consistent pattern of spatial variation in the three ecological indicators, and this was confirmed by the hot- and cold-spot analysis (Fig. 5). Both mapping approaches indicated higher species richness in the South-western German Bight (see Fig. 1 for place names) and towards the Central North Sea beyond the EEZ, with species richness generally lower at the Dogger Bank. N₁ showed a patchy distribution with highest values around the edge and outside of the EEZ. Within the EEZ and low N₁ values were most apparent around the Dogger Bank. Much of the study area featured a fish community consisting of a high proportion of smaller, fast-growing and fast-reproducing fish, resilient to fishing pressure. The CSI generally increased with depth and values were highest around the norther part of the Elbe River Glacial Valley and towards the Central North Sea. The fish community in these two locations would be the most vulnerable to additional fishing pressure (Fig 2).

The hot-spot analysis revealed that no grid node shared either a high or a low value across all three indicators, however, hot-spots (or cold-spots) where high (or low) values of at least two of the three indicators overlapped were apparent (Fig. 5).



Fig. 5. Statistically significant hot-spots (red) and cold-spots (blue) of all indirectly and directly mapped indicators (solid colours) and pairs of indicators (dashed lines) based on the Gertis-Ord-Gi* statistic along with Special Areas of Conservation of the Natura 2000 network and priority sites for offshore wind farm (OWF) developments (status January 2016).

The most obvious biodiversity cold-spot in Figure 5, covering the Dogger Bank and the transition zone between the Dogger Bank and the German Bight, also overlays one of the largest Natura 2000 MPAs established in the German EEZ. Conversely, one large hot-spot in the Elbe River Glacial Valley region, generated by overlapping high CSI and N₁ indicator values, is situated well to the northwest of the largest Natura 2000 MPA located in the Eastern German Bight. A second large hot-spot, caused by the overlap of two indicators and located towards the Central North Sea, again lies to the northwest of the large Dogger Bank Natura 2000 MPA. Figure 5 suggests that these two largest MPAs are likely to contribute little to the preservation of fish biodiversity in the German EEZ. Only one Natura 2000 MPA, the Borkum Reef Ground in the South-western German Bight overlapped with a fish biodiversity hot-spot, generated from overlapping high S and N1 indicator values. Only 1.7% or 5.9% (predicted by the indirect and direct mapping approach, respectively) of all the two-indicator hot-spot grid nodes in the German North Sea EEZ lay within designated MPAs, whereas the German Natura 2000 MPA network covers 26.8% of the area. Overlap of ecological indicator hot-spots with priority areas for future offshore wind farm development was minimal, suggesting that impact on the fish community from wind farm development at least at the EEZ scale is also likely to be minimal. However, both approaches revealed an overlap of a biodiversity hot-spot with one and two OWF, respectively, that are already at work.

Spatial variation in the N_1 index was strongly influenced by variation in the CPUE of the more abundant flatfish species. The biggest change in indicator values and patterns occurred when dab was excluded from N_1 calculation. This resulted in a staggering 84 % of altered grid node values. While the difference did not exceed +/- 1 index points in most cases, values were considerably higher (up to 7 index points) in several distinct areas in the southern and northern part of the EEZ, generating quite different patterns of N_1 distribution (Fig. 6). In contrast, the CSI was considerably more robust to variation in the abundance of dominant species; only 4 % of grid nodes showed higher values in near-coastal areas when the sand goby was excluded. The exclusion of all other species resulted in similar index values.



Fig. 6. Influence of individual species on N_1 (grey) and the CSI (green) as the percentage of grid nodes with different index values after each species is subsequently excluded from index recalculation. The map to the right exemplary shows the difference in N_1 index points that results from excluding dab from index calculation (N_1 - N_1 without dab).

4. Discussion

In this study we emphasise that maps of both approaches differed between indices, that both approaches did not accurately predict observed values and that the indirect mapping approach generally produced more detailed maps whereas the direct approach only indicated principle underlying patterns. However, CSI predictions by both approaches were more strongly correlated which may suggest that the mapping strategy has less impact on indicators with little variation and spread in the data. In the following, we discuss our results with respect to each mapping approaches' strengths and weaknesses, as well as potential opportunities to improve both approaches. We further summarise these discussion points in the SWOT analysis (Table 3) to provide some decision support on the choice of the appropriate approach. The greater level of variability in the indirectly modelled indices is the result of the stronger spatial aggregation of individual species distributions (higher spatial dependency) in comparison to the lower spatially aggregated and therefore smoother directly modelled indices (Table 2). Allowing for these individual species responses may thus be the biggest strength of the indirect approach. In addition, given how highly N₁ values were driven by the six most common species, abundance distribution maps are important for the interpretation of final index maps. The strong influence of these species was not surprising because they made up more than 90 % of the entire sample data of the GASEEZ survey. It was therefore more surprising that the CSI, which is also an abundance-weighted index, was significantly less influenced by highly abundant species. A possible explanation for this being that the individual SIs of these species are relatively similar (see Table 1), with the exception of the sand goby, whose exclusion from index calculation resulted in the only change of index values.

Without doubt, the biggest criticism of the indirect approach pertains to its use for communities with high zero-inflation, which is the case for our data set. While it is argued that this may be the rule for most ecological studies rather than the exception (Martin et al., 2005), excessive zeros were also deemed as a mere sampling artefact (McGill, 2003). As previously mentioned, modelling highly zero-inflated species is a challenge. When a (semi)variogramme analysis suggests a lack of spatial structure, the most appropriate surface to fit to the data is equal to the mean of all the values (ICES, 2015). However, most of the time distributional metrics are applied to the raw data, implicitly assuming that a spatial structure exists where a geostatistical approach would infer no such structure. This would only be appropriate if the survey design or data treatment (such as the aggregation of samples) was so comprehensive that observed data would be an adequate representation of the "true" unobserved diversity (Greenstreet and Piet, 2008; Gotelli and Colwell, 2001). The mean value approach is therefore a pragmatic way to tackle sampling and catchability issues by substituting zero-inflated species which are not routinely sampled in most surveys. However, decision rules have to be introduced to make this approach applicable in the future to overcome current arbitrariness with delineation from the distribution range based on the sampling data.

We further showed that map outputs with and without highly rare species with more than 95% zero catches basically resulted in identical maps. Given that these species did actually only occur once or twice this was to be expected. While we are not arguing the conservation importance of these species, these results show that they simply did not or hardly contribute to community-level index maps. In a conservation or spatial planning process, in which community-level maps are used, additional information on these species is therefore necessary to complement map outputs of indices. This is especially important for protected species, e.g. red list species (Thiel et al., 2013). We addressed this by mapping rare species occurrences from the survey data.

Approach	Strength	Weakness	Opportunities	Threats
Direct	 Includes all species in a data set Easy to display uncertainty Time- efficient analysis May detect shared patterns of species responses to environmenta l conditions 	Inaccurate due to smoothing Inaccurate due to non- additivity of indices (with most interpolation methods)	Using conditional simulations Using kriging of beta- diversity or modelling with environmental variables, e.g. (zero- inflated) GAM/GLM	Unstratified sampling design or imbalanced statistical model may lead to false significances with environmental
		Does not take sampling artefacts due to catchability issues into account	Using estimator of S that accounts for undetected species (e.g. Chao1/Chao2)	variables
		May show weak spatial structure or relationship to environmental variables based on assumption that all species respond to the environment in the same way (e.g. the functional form or shape of these responses is the same)		Overlooking biodiversity hotspots or areas with high variability
Indirect	 Allows individual species response (more realistic distribution of individual species) Can combine 	Rare species may not be included due to high zero- inflation, therefore based on limited number of species	If species cannot be modelled, the mean value approach may be used Influence of rare species on index may actually be negligible Map rare species' occurrences as supplement	Excluding species of special conservation concern
	models from different surveys – Produces	Display of uncertainty of prediction not straightforward	Uncertainty of indices: recalculate index with minimum and maximum predictions	
	additional information via individual species distribution – No additivity issues (with most interpolation methods)	Interpolation of individual species distributions may create false presences and condenses the range of species abundances leading to higher index values due to more even abundance distributions	Using conditional simulations or modelling with environmental variables, e.g. zero- inflated) GAM/GLM Interpolation gives less weight to extreme sampling events	Unstratified sampling design or imbalanced statistical model may lead to false significances with environmental variables; issues with zero-inflation may persist
		More time consuming	Possibility of automated fitting procedures	May lead to unrealistic models

Table 3. Summary of the SWOT analysis presenting main strengths and weaknesses of the direct and indirect mapping approach, as well as opportunities and related threats to address these weaknesses.

Species richness predicted using the indirect approach was much higher compared to observed values. This was however due to the mean value approach in which mean CPUE values of each species are assigned to each grid node. Also, the mean value approach increased the range between upper and lower prediction bounds. Most of these species mean CPUE values were very small (<= 1), so when we calculated the lower bound of indirectly predicted S, many of the rare species were not predicted to occur anymore. This explains the high difference between species richness predictions and the lower prediction bound. Likewise, some of the modelled species CPUE that were predicted not to occur in certain areas of the study site were suddenly present when we used the upper bound predictions. In addition, we applied a conservative approach by including all grid cells with CPUE values > 0in the analysis which has likely contributed to high S values in the indirect approach. However, the imprecision when compared to observed values and greater level of uncertainty for species richness predictions was to be expected for the indirect mapping in combination with the mean value approach because species presence and abundance are extrapolated beyond the limits of the data. Therefore, even though it may be counterintuitive, a strict comparison to observed values in this case should not be the main measure of output quality. In contrast, the direct approach did not accurately predict observed values either, despite being based on the raw sampling data; a reason being that the autocorrelation of the indices wasn't pronounced enough for the kriging procedure to adequately describe the spatial structure in the data.

As previously mentioned many studies have shown that the observed number and abundance of species is underestimated by most surveys because many species remain undetected due to an insufficient amount of sampling (Gotelli and Colwell, 2003). In fact, Greenstreet et al. (2007) calculated that at least 20 trawl samples from the IBTS survey (30 min with an 8 m beam trawl) had to be aggregated in order to arrive at estimates representative of the actual diversity per ICES statistical rectangles (1° x 0.5°). For our case study, such a survey design with more than 20 trawl samples per survey area is only implemented in the German Small-Scale Bottom Trawl Survey (GSBTS) which annually samples 12 fixed boxes of 10 x 10 nm across the North Sea and can therefore not be used for spatial interpolation at the EEZ scale. The GASEEZ survey used in this study has the best coverage for the German EEZ. Still, the fact that 25% of all species were only encountered once or twice suggests that these species do occur in other parts of the EEZ but have simply remained undetected (Gotelli and Colwell, 2003). Therefore, instead of deeming high indirectly predicted S values as overestimated, it may be a more accurate estimate or even still an underestimate of the actual number of species present. These sampling issues were not addressed in the direct approach since indices were calculated from the "raw" sample data. When metrics are derived this way, it is assumed that the fitted density at each sample location equals the observed sample density. It is therefore also assumed that a spatial structure is present, even though a (semi)variogramme analysis would infer that no such structure existed (ICES, 2015).

Kriging of indices produced very smooth maps that did not accurately predict observed values. In addition, Granger et al. (2015) recently deemed the direct approach based on kriging local diversity as inaccurate due to additivity issues. Kriging is based on linear combinations of sample values and thus assumes that the regional diversity is the sum of all local diversities. This however, would only be the case if two locations did not share a single species. Kriging of beta-diversity was thus suggested instead. Still, as previously discussed sampling issues persist if indices are derived from raw sample data. The kriging procedure may also introduce a bias in the indirect approach because, like most interpolation methods, it is based on averages of observations. Hence, kriging does not predict zero occurrences and therefore discontinuities in the distribution well. However, this may actually be beneficial for abundance weighted indices by reducing the influence of extreme sampling events such as sampling an aggregation of a particular species. For mobile species sampling is a representation of the distribution at a particular point in time; smoothing the abundance can therefore also be considered as a more realistic measure of a particular species abundance distribution.

Taking these points into account we recommend the indirect approach be used for our study site. However, there are also incidences in which the direct approach may be preferable (Table 3). Time-wise, for the number of species present in the study area, mapping effort was manageable. The distribution of species is actually one of the suggested MSFD indicators under the biodiversity descriptor 1. Having high quality maps of individual species can then be used to calculate most community-level indices with little additional effort. However, this should cause a significant workload in highly diverse systems with potentially hundreds of species. While certain studies suggested automated fitting procedures (Ferrier et al., 2002), these should be applied with great care as this generalises processes and may not provide the most realistic model (Table 3). However, in a setting with high species diversity and a high number of rarely encountered species having to exclude a large fraction of the community makes the indirect approach problematic in a conservation context. Here, the direct approach has some obvious advantages. In order to make the direct approach more applicable, we first suggest to use non-parametric estimators for species richness and diversity indices based on probability sampling theory (e.g. Chao1 and Chao2 for estimation of S) that take account of a species' different probability of being discovered in the sample (Chao and Shen, 2003; Gotelli and Chao, 2013). Then we suggest more sensitive modelling methods other than kriging to better display variability in the derived indices and to avoid non-additivity issues.

Conditional simulations or generalized additive or linear models (GAM/GLM) with abiotic and/or biotic variables are potential alternatives to kriging (Journel, 1974; Venables and Dichmont, 2004). Compared to kriging conditional simulations better represent variability in the data but issues with zero-inflation persist. GLMs and GAMs may be useful also because they can deal with a higher level of overdispersion such as zero-inflated Poisson GAMs (Agarwal et al., 2002; Lyashevska et al., 2016). Such models may contribute to more accurate predictions. However, especially GAMs are very data driven and infer likely habitats based on environmental factors. While the model can deem a variable significant this may in fact be an artefact of the sampling design and the data rather than explaining the system's actual variability. One would have to ensure to include the most explanatory environmental variables into the analysis with all environmental combinations equally represented (Guisan and Zimmermann, 2000). As previously mentioned, our initial tests using GAMs in combination with the direct approach to map taxonomic indices did not work well. While GAMs were more successfully used to directly predict diversity indices of demersal fish (Smoliński and Radtke, 2016), this method may not be a panacea. Other possibilities are hurdle approaches where a presence/absence model is combined with an abundance model of only the presence data (Welsh et al., 1996). Nevertheless, no matter which approach is applied certain species are too rare to be modelled.

As shown in the SWOT analysis, both mapping approaches have their respective advantages and pitfalls that are a function of the survey design, the spatial modelling method and the indicator chosen (Table 3). If sampling issues are accounted for, both approaches can be useful.

The overall different patterns between indicators stress the importance of assessing biodiversity based on a suit of indicators. It also shows that areas of higher sensitivity to fishing are not synonymous with areas of higher biodiversity. Mapping of the CSI in combination with taxonomic indices may therefore contribute to overcoming current challenges of integrating fisheries with biodiversity objectives (Thrush et al., 2015). The hot-spot analysis did uncovered areas with elevated or low values amongst two of the three indicators. This revealed that the two largest hot-spots of the EEZ would hardly be protected under Natura 2000 legislation. This may require a future revision of current environmental

legislation to remedy this shortcoming. The overall minimal overlap of hot-spots with OWFs may suggest a minimal future impact on fish biodiversity, but direct effects of introducing hard substrate into a soft bottom habitat in combination with a relocation of fishing effort is not well understood (Vandendriessche et al., 2015). While local changes in species composition may be expected, resulting effects at larger scales are still unknown. Although there was overlap between operational OWFs and high biodiversity, no causality can be inferred from this because the data used in this study was collected before the OWFs in question were operational. Biodiversity cold-spots occurred in the coastal areas which receive the highest level of fishing pressure in the German EEZ (Fock, 2008). Particularly the CSI showed low values in areas of high fishing pressure. A pressure-state analysis would be needed to corroborate these findings and to assess cause and effect between influencing factors of natural disturbance and fishing pressure on index values.

As for our case study area linkages between conservation and economic growth objectives are not well implemented. The German maritime spatial plan (BMVBS 2009) for example, was originally motivated by sectoral interests, despite its environmental imperative, to conserve biodiversity. However, current reality is that a structural ecosystem approach is clearly lacking (Jay et al., 2012). In case that the first revision cycle under the MSFD in 2018 may show that good environmental status of biodiversity has not been met, stronger linkages will have to be implemented between relevant instruments and institutions. In turn, this may lead to increased political will to better integrate biodiversity state into management decisions under MSP and the CFP. Here, the CSI may be a promising new tool by bridging fisheries with biodiversity science.

5. Conclusion

The motivation behind this study was to compare two principle mapping approaches based on three community-level biodiversity related indicators to assess which one produces more reliable information for implementing marine environmental legislation.

Based on the findings of this study, we recommend the indirect mapping approach in combination with the mean value approach be used in the German EEZ over the more general direct approach as it provides more detailed information and is less influenced by sampling artefacts. The direct mapping approach is a good way of conducting a quick analysis to identify main underlying patterns of spatial biodiversity. It is however questionable whether the lack of detail is sufficient as source of information in a decision-making or policy context. We were able to show that advocated drawbacks of the indirect approach, most of all having

to exclude highly zero-inflated species, could be remedied with the proposed mean value approach while the exclusion of very rare species did not affect indicator values. Nevertheless, supplementary information on the occurrence of these species should accompany final map outputs. It is therefore likely, that results are transferable to other North Sea countries or areas with a limited number of species. Accurately predicting spatial biodiversity patterns is not an easy task and the choice over the mapping approach cannot be generalised. Specifically, sampling issues need to be better accounted for and will require predictions that address different probabilities of species detection (Monk et al., 2012). Multispecies hierarchical models may be a way forward that explicitly incorporate true and false zeros in the detection process (Iknayan et al., 2014).

We conclude that established indicator suites such as the Hill's numbers in conjunction with indicators directly linked to key pressures like the CSI may provide a more complete and accessible picture of biodiversity state. It may thus be more compelling to decision makers. As previously mentioned, community-level indicators are currently not part of the monitoring programmes developed under the MSFD. Instead, species distribution ranges and patterns are used as surrogates. However, it is debatable whether such indicators without knowledge of community level processes are a true measure of biodiversity. Furthermore, community-level indicators can synthesise complex data into a simple index interpretable by decision-makers (Ferrier and Guisan 2006). Therefore we recommend mapping of community-level biodiversity indicators in addition to species-level indicators.

As this study has shown, the choice over the mapping approach can make a significant difference and scientific underpinnings of how to map biodiversity require more scientific attention and will have to be readily available for the relatively short-term information needs in political decision making. Here, standardisation of index calculation, data treatment and a protocol to adequately address sampling issues are needed to make biodiversity indicators comparable across study sites. To inform decision making, spatial pressure-state analyses with key pressures such as fishing or risk-based approaches with a less stringent link between state and pressure (Stelzenmüller et al., 2015a) should subsequently be tested to assess whether management can move from precautionary to predictive approaches (Naeem et al., 2012). Keeping in mind that the choice over the mapping approach matters, spatial information of community-level biodiversity indicators is an essential step to better integrate biodiversity conservation into marine spatial planning processes and therefore balancing conservation with economic growth objectives to safeguard marine biodiversity.

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Supplementary data

The following supplementary material is available at ICES JMS online: predicted CPUE distribution maps of 19 demersal fish species based on ordinary kriging of GASEEZ survey data (Appendix S1) and a map with presence data from 18 highly rare species and their species specific sensitivity indices (SI) that were excluded from the indirect mapping approach (Appendix S2). The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.



Appendix S1. Predicted CPUE distributions of 19 species per 15 min trawling in the German EEZ of the North Sea and adjacent waters from the kriging procedure of combined GASEEZ data of 2005, 2009 and 2013. The six distributions at the top are the most abundant species and are thus scaled differently as the remaining 13 species.



Appendix S2 Presence of 18 rare species that had to be excluded from the indirect analysis due to their highly zero-inflated occurrences. The color code represents the species' specific sensitivity indices (SI) against additional fishing pressure with increasing sensitivity from resilient (blue) to sensitive (red).

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Chapter 3

Disentangling fishing from habitat effects to explain spatial patterns in fish community sensitivity to fisheries

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Abstract

Understanding the relationship between pressures and states is a prerequisite of most indicator-based management schemes, e.g. such as under the Marine Strategy Framework Directive. Here, biodiversity is a central indicator. However, opinions diverge whether anthropogenic pressures can be disentangled from other environmental factors. Also, specifically at the community-level effects of fishing on fish biodiversity have never been fully understood. One reason for that is that most established taxonomic biodiversity indices are not coupled to fishing pressure. We developed a functional trait-based indicator, the community sensitivity index to fishing (CSI) for the North Sea demersal fish community, which is derived from traits that are sensitive to fishing. We first used a correlative approach to test the spatial relationship of the CSI in German waters of the North Sea with fishing effort interpolated from Vessel Monitoring System data of the main international bottom trawl fleets and depth. We structured our analysis according to different spatial scales and differentiated between fleet-specific and combined effects of bottom trawling. To disentangle habitat from fishing effects and analyse potential thresholds we used generalized additive models (GAM) and classification and regression trees (CART). All approaches showed that relationships were highly fleet- and habitat-specific. The CSI showed expected pressure-state patterns (a decrease of index value with increase in fishing effort) with beam trawling effort and was most influenced by depth. Specifically for the coastal small beam trawl fleet, fishing and depth both explained about 25 % each of the variability in the CSI. This relationship was reversed for the otter trawl fleet, where the co-correlation between trawling activities on certain habitats and depth strata as well the depth and habitat-related community structure confounded interpretation of the results. The CSI proofed to be a valid surveillance indicator but its full operationalisation towards a pressure-state indicator for management requires carefully designed experimental studies on its responsiveness to fishing. The results further suggest that a century of commercial fishing has shaped the fish community towards species with resilient traits against fishing. However, without a comparison to historical data it is difficult to project the impact of future trawling activities. Therefore, we suggest a more general assessment using environmental risk-based approaches that can quantify effects and impacts of management scenarios and address uncertainties.

Keywords: Trawling, VMS, sensitivity, community sensitivity index, trait-based indicator, demersal fish, pressure-state relationship, spatial statistics
1. Introduction

Changes in marine ecosystems and negative impacts of declining marine biodiversity on the ocean's processes, its resilience, goods and services have been documented worldwide (Lotze et al. 2006; Worm et al. 2006; Butchart et al. 2010; Hooper et al. 2012). While multiple anthropogenic and climate-related drivers have been attributed to these changes (Halpern et al. 2008), fishing remains one of the greatest pressures in marine ecosystems, causing changes in the composition, size structure and trophic structure of fish assemblages and by removing whole functional groups from the system (Costello et al. 2010; Martins et al. 2012; Thrush et al. 2015). In addition, trawling causes indirect effects through alteration of habitat, prey availability and quality (Kaiser et al. 2002; Hiddink et al. 2016). In fact, fishing makes up the bulk of the human footprint on marine ecosystems in Europe (Foden et al. 2011). However, the integration of fisheries and biodiversity objectives poses ongoing challenges (Schmiing et al. 2014). Halting the decline of marine biodiversity has become a key policy priority spearheaded by the MSFD in Europe under which a monitoring programme was set up by each member state based on pressure and state indicators. Such pressure-state relationships are state-of-the-art for integrated marine assessments in Europe (Fock, 2011). In addition, marine spatial planning (MSP) is being implemented as a cross-cutting approach to achieve sustainable development in a competitive environment. In order to inform both, the MSFD and MSP, information and subsequent relationships need to be assessed spatially at management relevant scales and fine enough resolution.

Considerable effort was dedicated to defining, testing and evaluating indicators to monitor the pressures on, and status of exploited marine ecosystems (Coll et al. 2016) and to develop thresholds, preliminary reference levels or directions for management advice (Link et al. 2010; Samhouri et al. 2010; Shin et al. 2010; Large et al. 2013). Three types of state indicators have been defined: 1) the relationship between pressure and state is not well understood, 2) the relationship is understood but only in terms of a reference direction and 3) the relationship is fully operational including a target level (Rochet & Trenkel 2003). Fully operational community level indicators are rare; the large fish indicator (LFI) (Greenstreet et al. 2010) being part of OSPAR's Ecological Quality Objectives and the AZTI Marine Biotic Index (AMBI) (Borja et al. 2000) describing the status of benthic communities are among the Specifically for taxonomic community-level exceptions. biodiversity indicators operationalised pressure-state relationships remain elusive despite a wealth in available indicators.

To date, various studies testing the relationship between fishing pressure and biodiversity indicators across the North Sea and have found equivocal results (Greenstreet & Hall 1996; Rogers et al. 1999; Callaway et al. 2002; Piet & Jennings 2005). Therefore, these indicators scored poorly against identified selection criteria (Rice & Rochet 2005) and were not included in current European biodiversity monitoring programs in support of the MSFD (Greenstreet 2008). A contributing factor may be that there is no ecological link between the indicator and the pressure.

Metrics of functional diversity have recently been found to complement traditional metrics of species diversity (Cadotte et al. 2011; Stuart-Smith et al. 2013) and may offer greater explanatory power than traditional taxonomic-based indicators when it comes to explaining community responses to disturbance such as fishing (Mouillot et al. 2013). We therefore used the community sensitivity to fishing index (CSI) specifically to address this shortcoming (Rambo et al, in press). The CSI is based on live-history traits such as ultimate body length, growth rate and age- and length-at-first-maturity, which have been empirically identified as an indicator for a species' sensitivity to additional mortality from fishing pressure (Jennings et al. 1999; Greenstreet et al. 2012; Le Quesne & Jennings 2012). The assumption behind the CSI is that the proportion of average ultimate body length, size and age at maturity of fish in the groundfish assemblage should be least while growth rates should be highest in highly fished areas. All variables result from first-order effects of fishing as a source of mortality that is not equal across all species and sizes of fish in the community. Thus, mapping areas of higher fish sensitivity to fishing may help to address the challenge of integrating fisheries management with biodiversity conservation objectives.

Most analyses of fishing pressure and biodiversity state have focussed on temporal changes or were conducted at large spatial scales (ICES rectangles) not useful in an MSP context. In addition, previous analyses have often neglected to include environmental gradients as source of community distribution and fishing activity. However, environmental gradients drive the distribution of fish assemblages. Numerous studies have investigated the association of bottom fish assemblages to environmental drivers in the North Sea and described depth, sea bottom temperature (SBT), sediment and hydrographic regimes amongst the most influencing factors (Daan et al. 1990; Greenstreet & Hall 1996; Callaway et al. 2002; Ehrich et al. 2009). In return, trawling distribution often concentrates patchily along certain depth strata or in certain habitats where target species abundances are highest. Therefore, environmental effects need to be separated from pure fishing effects (Pommer et al. 2016; Farriols et al. 2017). Different fishing gears affect the environment as well as fish assemblages in different ways (Depestele et al. 2014) which needs to be factored into the analysis as well.

Generally, pressure-state analyses have certain pitfalls. Pressure and state indicators may not be fully linked and the state of an indicator may not be a direct and sole consequence of one pressure (Fock et al. 2011). With this study we widened the univariate approach and included natural variability as driver of indicator state. First of all, we tested the quality of the CSI to describe spatial pressure-state relationships along gear-specific trawling gradients and habitats in German waters of the North Sea to inform spatial management and conservation as part of a MSP/MSFD process. Specifically, we tested the hypothesis whether the CSI would decline along a gradient of fishing pressure using correlation. We further used regression based techniques to determine individual contributions of fishing and environmental variables to explaining variability in the CSI and to derive potential fleet-specific target levels for full operationalisation. Finally, we discuss our results in the light of the MSFD and MSP management process.

2. Material & methods

2.1 Study site and the CSI

We conducted our study in the German Exclusive Economic Zone (EEZ) of the North Sea and adjacent waters (see Fig. 1). We used species abundance distribution maps from Rambo et al. (in press) to spatially represent the CSI. These maps were based on aggregated CPUE data (catch per 15 min beam trawling) from the German Autumn Survey of the EEZ (GASEEZ) (Fig. 1a) considering years with best spatial coverage only (2005, 2009 and 2013). CPUE was interpolated onto a grid with a grid cell resolution of 5 x 5 km using ordinary kriging. The primary objective of this monitoring programme is to assess spatial and temporal changes in local fish communities associated with human exploitation (Neumann et al. 2013). In order to reduce the influence of highly abundant species, we square root transformed CPUE prior to index calculation. We then used the indirect mapping approach outlined in Rambo et al (in press) in which index values are derived per grid cell from stacked distribution maps (Fig.1d). The CSI is computed as a sum of species specific sensitivity indices (SIs) published in Greenstreet et al. (2012), weighted by the individual species' CPUE, and standardised by the total number of individuals caught: $CSI = \frac{\sum_{i=1}^{n} n_i SI_i}{N}$, where n_i is the number of individuals of species i, N is the total number of individuals and SI_i is the SI of species i. The SIs are based on ultimate body length, the growth parameter k, and length- and age-at-first-maturity. These traits are closely linked with a species' capacity to cope with additional fishing mortality (Jennings et al. 1998; Jennings et al. 1999; Le Quesne & Jennings 2012). For certain species,

SIs were not available and these were derived from the formulae presented in Greenstreet at al. (2012). Individual species' SIs have been classified into three categories: resilient (> 0 – 0.164), intermediate (0.165 – 0.31) and sensitive (0.311 – 1), we therefore apply this logic to the CSI, also. Hence, the CSI ranges from 0, corresponding to an empty net, to 1, corresponding to catching only the most sensitive species (Greenland shark).



Fig. 1. Environmental variables used in subsequent analyses of the study area (the German EEZ of the North Sea and adjacent coastal waters) showing a) habitat types redrawn from Rachor and Nehmer (2003) [A: Eastern German Bight, B: Inner German Bight, C: South-western German Bight, D: North-western German Bight, E: Elbe River Glacial Valley, F: Transition zone between German Bight and Dogger Bank, G: Dogger Bank, H: Central North Sea], dots represent sampling stations of the GASEEZ survey used to derived the indicator map, winter water masses redrawn from Laevastu (1962); b) depth obtained from the BSH (www.bsh.de); c) average December sea bottom temperature (SBT) derived from Núñez-Riboni & Akimova (2015); and the d) the community sensitivity index to fishing (CSI) from Rambo et al. (in press).

In total 30 species were considered for index calculation while highly rare species could not be spatially represented and were therefore excluded from index calculation (see Rambo et al. (in press) for more details). According to their frequency of occurrence, the SIs show a slight trend towards increasing sensitivity to fishing with decreasing abundance (Fig. 2).



Fig. 2. Species used to derive the indicator maps ranked according to their square-root transformed CPUE (from left to right) from the entire dataset. Each species' sensitivity index (SI) from Greenstreet et al. (2012) are provided and colours indicate whether a species is resilient (0.09 - 0.165), intermediately sensitive (0.165 - 0.31), or sensitive (0.311 - 1) to additional fishing mortality.

We further explored the relationship between these species and eight specific habitat types of the German EEZ of the North Sea identified by Rachor and Nehmer (2003) (Fig. 1a). These habitat types were derived from combinations of abiotic and biotic variables (depth, grain size, salinity, currents, distance to shore, as well as trophic and biological parameters such as inorganic nutrients, turbidity, primary production and the presence of reef-building or habitat structuring organisms. We explored the spatial relationship using non-metric multidimensional scaling (NMDS) plots. We applied square root transformation to the data and calculated the Bray-Curtis distances for the species-by-habitat-type matrix using the R-language function "metaMDS" available in the vegan package (Oksanen et al. 2016); for a detailed description of NMDS analysis, see Clarke and Warwick (1998).

2.2 *Mapping of fishing pressure*

In European waters fishing vessels above a length of 15 m, since 2012 above a length of 12 m, need to be equipped with a Vessel Monitoring System (VMS). VMS data were initially

collected for the purpose of control and enforcement of fisheries under legislation introduced by the European Commission (EC 1997) to provide information on vessel position, speed and heading. The VMS transmits at regular intervals of approximately every 2 hours but with higher polling rates for some countries. For our study area, data from all European vessels are available. Further, the majority of fishing activities in offshore waters (waters beyond the 12 nautical mile zone) are from vessels equal to or exceeding the overall length of 15 m, respectively. Thus derived estimations about fishing pressures are assumed to be representative.

In its raw format, VMS data are geographically distinct points, so-called "pings", and no distinction is made between transmission during fishing, steaming or floating. If these VMS pings are linked to the corresponding logbook data information about the ship, the applied gear and eventually also the catch can be obtained. For those nations, where logbook data were not readily available (here: all ships not registered in Germany), ships were identified via the European Fishing Fleet register (http://ec.europa.eu/fisheries/fleet), and information about ship size, engine power and the primary gear was extracted. Note that these are the gear types registered to the vessel but some vessels actually change the gear throughout the year.

Data were subsequently analysed with the VMStools package (Hintzen et al. 2014) and the software R 3.0.3 (R Core Team 2013). VMS data were cleaned according to the methodology described by Hintzen et al. (2012) to identify technical problems, duplicates and signals from ports. To identify the vessel state as steaming, fishing or floating, speed frequency histograms were analysed with the methods "activityTacsatAnalyse" and "activityTacsat". Speed boundaries were calculated and only records where the vessel was assumed to be fishing were included in the following. The applied algorithm is usually quite effective estimating speed intervals for towed gears, and here, only beam and otter trawls, as the two dominating mobile bottom-contacting gears in the German EEZ of the North Sea, were considered.

Logbook information was not available for the international fleet, hence we distinguished fishing segments on métier level 4 (EC 2008), i.e. gear type. Further, small and large beam trawlers were separated by engine power (><221 kW), which is in accordance to the regulation of the plaice box (EC 1998). By this definition the near-coastal shrimp fishery with small beam trawls could be largely distinguished from the more-offshore flatfish fishery, mainly targeting sole and plaice, with larger and also heavier beam trawls. We depicted these fleets separately because both operate in different areas and sensitivity of ecosystem components is gear specific (Depestele et al. 2014).

To estimate a spatially resolved fishing pressure index we followed the swept area approach, which is based on gear width information. However, this is not routinely recorded in logbooks, and average beam widths were therefore estimated from fisheries observer protocols of the German North Sea fleet. The analysis of 18 monitored vessels (2002-2014) resulted in an average single beam width of 8.3 m for vessels smaller 24 m overall length or 221kW engine power, and 11.3m for vessels larger than that. Beam widths were multiplied by two because two beam trawls are usually operated in parallel. For otter trawls targeting demersal fish the footprint size was estimated according to Eigaard et al. (2016), assuming a linear relationship between vessel size and door spread: door spread= 9.6054* kW^{0.4337}.

For predicting the trawl path from VMS point data, we interpolated 98 points between two succeeding fishing pings with the cubic Hermit spline method (Hintzen et al. 2010). Hintzen et al (2010) found this method to provide a better estimate of the true track length than those estimates calculated from a straight line interpolation and underestimation of the true track length is on average less than 3 %. The distance between spatial fishing points was then multiplied with the corresponding gear width to calculate swept area values. These values were finally aggregated on a 5 x 5 km grid for the years 2010 to 2012 and divided by three to get a gear-specific average annual swept area per grid cell. We chose an average value because the number of registered fleets and therefore the VMS effort level is still increasing, to account for the otherwise misleading increase in effort (Hintzen et al. 2012).

Bottom trawling patterns in the study area have been relatively consistent between years and main effort per fleet is concentrated in easily distinguishable areas (Fock 2008). However, effort between fleets does overlap to a certain degree. To separate effects from all fleets we defined core fishing areas as those grid cells where a respective fleet exerted at least 60 % of the entire effort with a minimum fishing effort of 0.05 SAR to exclude non-fished areas but to still provide a gradient of different effort levels. The latter being the reason why we did not choose other proposed methods to derive principle fishing areas (Fock 2008). It has been suggested that relationships in chronically fished area are harder to quantify and that effects are more apparent in less frequently trawled areas (Farriols et al. 2017). Hence, we calculated the coefficient of range (CoR) of the entire trawl fleet as well as for each fleet to determine a relative measure of spatial dispersion or variability in fishing effort. The CoR is derived by dividing the difference from the sum of maximum and minimum effort for each grid node SAR_{max}-SAR_{min}/ SAR_{max}+SAR_{min}.

2.3 Spatially resolved pressure-state relationships

We used correlation and regression-based approaches to quantify spatial pressure state relationships between the CSI and fishing. After mapping the CSI and trawling effort onto our study grid, we correlated index values at each grid node versus fishing effort and habitat type. We used the total effort of mobile bottom contacting gears for the entire study area and habitat types as well as fleet specific effort for the core fishing areas. Data were presented as depth-stratified scatterplots with a loess smoother based on locally-weighted polynomial regression. We then applied several analytical methods to disentangle habitat from fishing effects with the help of classification and regression trees (CART) and generalized additive models (GAM). Here, we used depth and sediment structure (www.bsh.de), average December SBT derived from 2010 - 2012 (Núñez-Riboni & Akimova 2015), habitat types (Rachor and Nehmer, 2003) and winter water masses (Laevastu, 1962) in addition to swept area ratio (SAR) to test the relationship between the CSI, fishing and the environment.

CART is a very flexible multi-variate technique that searches for the value of one of the predictor variables that explains the greatest amount of variation in the response variable. The observations are split into two groups at each node according to splitting criteria until the tree reaches a size that balances predictive power and parsimony. CART techniques were made popular by Breiman (1984) and have since then also been applied to model species or community-environment relationships (De'ath & Fabricius 2000; De'ath 2002; Pesch et al. 2008; Yates et al. 2016). We used the R package "rpart" (Therneau et al. 2015) to build CARTs by letting each tree grow till its full length and applying a model selection based on a cross-validation procedure to balance predictive power and parsimony. This procedure follows the "1 – SE rule" in which a tree is pruned to the number of splits that is within 1 standard deviation of the best model's cross validation error (Breiman et al. 1984; Guisan & Zimmermann 2000).

CART can be used to provide complementary solutions to regression methods such as GAMs (Guisan et al. 2006). We used CART to derive cut-off values for trawling that would potentially lead to CSI decline while GAM analysis was performed to assess the overall importance of trawling to explain the variability in the CSI data. We used gamma distributed GAMs with a log link function in the R mgcv package (Wood 2016) to allow for non-linearity in the data. We followed the procedure described in Zuur (2010) according to data exploration, model formulation, selection and validation. We accounted for overfitting of data by adjusting the splines to 5 degrees of freedom. We did not include possible interactions

between the environmental variables since we attempted to assess individual contributions of each variable. We applied a step-wise backward selection procedure and chose the final model based on the lowest Akaike Information Criterion (AIC) value, ANOVA results as well as residual and response plots. The final model included SBT (averaged from the three survey years used to calculate the CSI), depth, fishing effort (SAR) and habitat types: $CSI_i = s(SBT_i)$ + $s(depth_i) + s(SAR)$ + habitat.type + ε_i , where ε_i is Gamma distributed.

In order to assess the relative contribution of each variable to explaining the variation in the CSI data, we calculated the proportion of deviance explained by each term. If relationships are non-linear, (partial) variance in the CSI distribution can be partitioned using (partial) GAMs based on all possible combinations of predictor variables similar to the approach presented in Peltonen (2007).

Variation partitioning with three explanatory matrices has been described in detail by Liu (1997), Anderson and Gribble (1998), and Heikkinen et al. (2004). Having four explanatory variables led to 14 different models in addition to the full (mf) and null model (m0), describing the (m1) pure effect of fishing, (m2) pure effect of depth, (m3) pure effect of SBT, (m4) pure effect of habitat type, the combined effects from (m12) fishing and depth, (m13) fishing and SBT, (m14) fishing and habitat type, (m23) depth and SBT, (m24) depth and habitat type, (m34) SBT and habitat type, and effects from the three groups of explanatory variables, (m123) fishing, depth and SBT, (m124) fishing, depth and habitat type, (m134) fishing, SBT and habitat type, and (m234) depth, SBT and habitat type. We calculated each model while keeping the smoothing parameters fixed, i.e. we used the same smoothers in the reduced models as in the full model to avoid changes in smoothers when correlated variables are dropped. Then, the deviance of each univariate model was subtracted from the full model, the null model, and each model combination that contained the variable of the univariates model divided by the number of alternatives (in this case 3). This resulted in eight proportions of explained deviance (ED) for each variable, here exemplary for habitat type: ED(m123)-ED(mf); ED(m0)-ED(m1); (ED(m2)-EB(m12))/3;(ED(m3)-EB(m13))/3;(ED(m4)-EB(m14))/3;(ED(m2)-EB(m24))/3;(ED(m3)-EB(m34))/3;(ED(m12)-EB(m124))/3;(ED(m13)-EB(m134))/3 and (ED(m23)-EB(m234))/3. Finally, we averaged the alternative deviances from all four variables so they would add up to the explained deviance from the full model by summing them up and dividing them by four multiplied by the deviance of the null model.

3. Results

3.1 Species-habitat relationship and fishing effort

The NMDS plot showed a clear structuring of habitat types from onshore to offshore (left to right) and confirmed a clustering of species with generally lower (resilient) SIs in coastal habitats (A - C) than in further offshore area (F - H) (Fig. 3). The very low stress value of 0.013 indicates a very good representation of values in reduced dimensions.



Fig. 3. Two-dimensional non-metric multidimensional scaling (NMDS) plot based on Bray-Curtis distance of square root transformed abundances of all 30 species included to derive the indicator maps. Capital letters indicated habitat types from Rachor and Nehmer (2003). The stress value of is a measure of model quality.

Small beam trawl effort was found to exert the most overall trawling effort per core fishing area with a single grid cell being completely trawled on average 1.22 times per year (Table 1). The most targeted habitats were the Eastern German Bight (A), North-western German Bight (D) and the Elbe River Glacial Valley (E) which are mainly trawled by small beam trawls, large beam trawls and otter board trawls, respectively.

Table 1. Minimum, mean, maximum and total swept area ratio [SAR] of mean annual international trawling effort per 5 x 5 km grid cell per habitat type (A - H) after Rachor and Nehmer (2003) and per trawl fleet (BTS: small beam trawls (< 221 kW); BTL: large beam trawls (> 221 kW); OBT: otter board trawls) as well as from each respective core fishing area.

	Trawling [SAR]												
	Habitat type								Core	Core fishing area			
	Α	В	С	D	Ε	F	G	Н	BTS	BTL	OBT		
Min	0.02	0.04	0.02	0.1	0.06	0.09	0.21	0	0.05	0.06	0.06		
Mean	0.95	1.19	0.89	0.72	1.01	0.36	0.53	0.16	1.22	0.46	0.69		
Max	4.56	5.8	5.17	6.82	4.06	0.91	1.02	0.56	5.79	2.03	6.28		
Total	337.9	121.6	105	277	234.4	61.2	44.5	6	433.8	217.9	252.8		
Total BTS	250.5	111.4	90.5	5.8	19	2.1	0.25	0					
Total BTL	5.4	2.7	8	196.2	51	9.8	25.2	2.2					
Total OTB	82	7.5	6.5	75	164.4	49.3	19.1	3.8					

3.2 Correlative analysis

The CSI showed signs of lower values with increases in total fishing effort, however, with considerable variability (Fig. 4). The fleet-specific plots across the entire study area showed a clearer picture. We found a strong decrease in CSI values with increasing fishing pressure for small beam trawlers, where the loess smoother suggested an exponential decline and, less pronounced, also for large beam trawlers. Results for both beam trawl fleets suggested that basically in all areas of medium to high fishing pressure (> 0.8 SAR), the CSI was below 0.165 corresponding to a demersal fish assemblage considered highly resilient against fishing. In other words, small bodied, early reproducing and fast growing individuals dominated the community, whereas in areas with less fishing pressure, the CSI suggested an intermediately sensitive community and therefore proportionally more large-growing, late-reproducing species. This was however not the case for the otter board trawl fleet where data clusters indicated that CSI values remained stable along a gradient of fishing pressure (1 – 6.2 SAR).

The plots from core fishing areas showed overall similar patterns, however, it became apparent that the CSI versus small beam trawls only declined in more coastal areas and that decline was not uniform. A decrease in CSI values with increases in large beam trawl effort became less obvious and also revealed two clusters with higher CSI values in lower fished areas. We then traced the locations of these data clusters and found that they represented specific areas in the study area (marked by number 1 to 6 in the plots and corresponding effort maps of Fig. 4). All but the large beam trawl plots showed a depth gradient with generally higher CSI values in deeper generally more offshore waters which confirming NMDS results.

Scatterplots of CSI values versus the coefficient of range (CoR) showed equivocal patterns with a lot of variability in the data, preventing a clear response to variability in fishing effort to be detected (supplementary information, Fig. S1).



Fig. 4. Community sensitivity index (CSI) versus mean annual international swept area ratio (SAR) of all, small (<221 HP) and large (>221 HP) beam trawls and otter board trawls across the German North Sea EEZ and adjacent waters [top panel] and per fleet-specific core fishing area only [mid panel]. SAR was based on aggregated vessel monitoring system (VMS) data from 2010-2012 of the main mobile bottom contacting gears, or of separate fleets within their respective core fishing areas (striped areas in right panels). Red lines are loess smoother based on locally-weighted polynomial regression and data points, each representing a grid node from the study grid, are coloured according to five different depth strata. The numbers (1 - 6) in the CSI vs. SAR plots [mid panel] correspond to the numbers in the map [bottom panel] indicating the spatial location of the data points.

The separate investigation of CSI values versus total trawling effort per habitat type provided more insights into some of the previously observed responses (Fig. 5). First of all, it showed that the strongest negative response to fishing effort occurred in the Eastern and Inner German Bight (A+B), while the South-western and North-western German Bight (C+D) showed less decline. In contrast, CSI increased with effort in the Elbe River Glacial Valley and the Transition zone towards the Dogger Bank (E+F), where otter trawl effort is concentrated. Across the Dogger Bank and towards the Central North Sea (G+H) CSI values seemed to decrease with increases in fishing also, however due to the relatively low gradient in fishing pressure this was not clear.

We then analysed the habitat composition between A and C specifically to explain why the decrease in CSI values was more pronounced in the Eastern German Bight (A) but less so in the South-western German Bight (C) despite both representing coastal areas with similar sediment structure and depth range. The latter is however closer to the English Channel with potentially more Lusitanian species influx. We found that species composition was fairly similar with the exception of Brill which occurred in habitat C but not A. Observed patterns were driven by a difference in CPUE of the three most abundant species; while in C dab and plaice dominated, there was a high abundance of sand goby in habitat A, which features one of the lowest SI across German North Sea waters.



Fig. 5. CSI values versus total swept area ratio of the main bottom contacting gears in different habitat types [A: Eastern German Bight, B: Inner German Bight, C: South-western German Bight, D: Northwestern German Bight, E: Elbe River Glacial Valley, F: Transition zone between German Bight and Dogger Bank, G: Dogger Bank, H: Central North Sea] redrawn from Rachor and Nehmer (2003). The red line is a loess smoother based on locally weighted regression. Data points, each representing a grid node from the study grid, are coloured according to five different depth strata. The numbers (1 - 6) in the CSI vs. SAR plots correspond to the numbers in Fig. 4.

3.3 Regression-based analysis

The CART and GAM analysis per habitat type revealed that trawling did in fact not significantly contribute to explaining the variability in the CSI along the Dogger Bank and the Central North Sea (Supplementary information, Fig. S2 & S3). In both habitat types depth was the most important driver of community sensitivity. Also, smoothers for trawling from bivariate Gamma distributed GAMs $CSI_i = s(depth_i) + s(SAR) + \varepsilon_i$, showed only marginal decrease of CSI values with increases in trawling effort in these two habitats (Supplementary information, Fig. S3). In contrast, trawling was highly significant (< 0.0001) in coastal areas (A – D) in explaining decreasing patterns of the CSI even when depth and / or SBT effects were removed.

The CART analysis of CSI values per core fishing area confirmed first results from scatterplots (Fig 6). Depth was the dominant variable (first split) for the small beam trawl fleet while trawling explained most of the residual variance in the data. In waters deeper than 18.5 m CSI values were reduced from 0.155 to 0.15 (5 %) in areas that were trawled more than 75 % per year (> 0.75 SAR). In waters shallower than 18.5 m CSI values were 8 % lower in areas that were trawled at least once per year (> 0.987 SAR). For large beam trawls habitat type explained most of the variance in the data with trawling > 0.666 SAR leading to lower CSI values in deeper waters (> 39.5 m) of the South-western and North-western German Bight (C & D). In contrast, lower CSI values were found in habitat type A and D where otter board trawling was less than 0.18 SAR. Water masses and sediment structure were not selected in the final models. Model quality was good with R^2 values ranging from 0.72 to 0.81. CART results from the entire survey area with combined bottom trawl effort (not shown) revealed that trawling was not among the explanatory variables. In contrast, depth was the most explanatory variables in the German Bight (A - D), while SBT explained more variability in CSI values in the remaining areas (E - F). When we repeated the analysis with fleet-specific effort (Fig. 6) small beam trawl effort of roughly 1 (>= 0.956 SAR) lead to a decrease in CSI values, in areas of the German Bight (A - D) that experienced no large beam trawl effort.



Fig. 6. Visual results from the CART analysis, relating the CSI with fishing effort, water depth, habitat type, sediment structure and winter SBT. Analyses were performed for the entire study area (all trawls, top left plot) and for each of the core fishing areas with the respective main fishing fleet (small beam trawls, large beam trawls, otter board trawls; from top right to bottom right). Each node shows the predicted value and the percentage of observations in the node, as well as all variables that were used to grow the best tree model along with the values at which a split is made. The R2 value indicates model quality.

To decompose potential synergistic effects between effort and depth but also other influencing variables such as SBT and habitat type we ran full models, univariate models and finally partial GAMs. As expected, SAR explained most for small beam trawlers namely 44 % from the univariate model (Table 2) and 24 % in the full model (Fig. 7). Both smoothers, univariate and from the full model showed an instantaneous decline with fishing pressure (Table. 2 & Supplementary info, Fig. S4). Even though, depth explained more of the variability in CSI values alone, when it was dropped from the full model deviance explained was only reduced by 4.5 % in comparison to SAR with – 10.6%. GAM results were overall congruent with the CART analysis while GAM models explained slightly more variability in CSI values, especially for otter board trawls (85.6 %, R²: 0.854). CSI in the core fishing area of otter trawls was mostly explained by habitat and depth with trawling only accounting for 7.2 % of the overall explained deviance (Fig. 7). SBT and habitat type explained most of the variability in the large beam trawl core fishing area with only 4.7 % of deviance from partial GAMs even though smoothers from the full and univariate models suggested a decline with of CSI values with increasing pressure.

Table 2. GAM results between the CSI and each fishing fleet from the full model including all variables and the univariate models showing the goodness of fit based on the Akaike Information Criterion (AIC) and the explained deviance (ED), as well as the ED if each variable is dropped from the full model (ED drop) and the direction of the smoother (trend) fitted from the full model. All model components were highly significant (p < 0.0001).

Core fishing area	Model	AIC	ED [%]	ED [%] drop	Direction of trend*
Small beam trawls	Full model	-2890	76.8	-	-
	SAR only	-2593	44.1	-10.6	Decrease
	Depth only	-2670	55.3	-4.5	Increase
	SBT only	-2506	26.7	-3.6	Increase
	Habitat type only	-2445	13	-13.9	-
Large beam trawls	Full model	-3922	82.3	-	-
	SAR only	-3169	11.0	-1.1	Decrease
	Depth only	-3172	12.2	-4.3	Increase
	SBT only	-3645	71.7	-2.9	Decrease
	Habitat type only	-3743	77.1	-4.4	-
Otter board trawls	Full model	-3058	85.6	-	-
	SAR only	-2428	12.4	-1.9	Bimodal
	Depth only	-2715	60.3	-8.4	Increase
	SBT only	-2482	24.4	-5.5	Decrease
	Habitat type only	-2712	60.4	-5.8	-

*Direction of trend refers to the smoother from the full model (Supplementay information, Fig. S4)



Fig. 7. Partial GAM results showing each variable's (trawling, depth, sea bottom temperature (SBT) and habitat type) individual contribution [percent] to explaining the variability in the CSI for each fleet seperately within each core fishing area.

4. Discussion

The main aim of our study was to test whether the CSI could be fully operationalised as a community-level state indicator as part of a pressure-state monitoring programme to provide management advice in an ecosystem-based management context to inform both MSFD and MSP. We tested whether the CSI declined along a gradient of fishing pressure and whether environmental influences could be separated in a way that would allow for a clear attribution of observed patterns to trawling. Results showed that an overall decline with increases in fishing effort after environmental signals were removed only occurred for small beam trawls as well as in more coastal habitats of the German Bight.

So why did anticipated patterns only occur in combination with the small beam trawl fleet and why did we not find a similar decline in CSI in further offshore areas? The fact that small beam trawls mostly operate in coastal waters makes this the proverbial chicken-or-egg question whether fishing or habitat is the main driver. Mean SAR of small beam trawls were three times and two times higher than that of large beam trawls and otter board trawls, respectively which might be a reason for the overall declining patterns. However, we did not account for differences in impact between gears. All three gears exert different pressures on the benthic system and are selective towards different size classes and/ or species. SAR represents a good common measure (area trawled) to compare fleet-specific fishing pressure and is thus a better indicator than effort hours still often used. Due to the aforementioned differences in gear an impact factor could be included in the future or ideally fishing mortality could be used which is however not always available for non-target species (Piet et al. 2007).

A common problem encountered in pressure-state analyses is that fishing pressure is often correlated with abundance of target fish which can mask a signal of declining abundances (Rose & Kulka 1999). Most of commercially caught fish species for human consumption are slow growing, large bodied and therefore more sensitive to fishing pressure (a higher SI). This may explain why especially for otter trawls, CSI did not decline in certain areas where fishing pressure was high. Those areas (indicated with numbers 4 - 6 in Fig. 4) are in fact traditional fishing grounds for otter board trawlers which have been exploited for at least a century (Fock 2008). In these areas a potential stable state against fishing effort seems to have occurred (Beisner et al. 2003). This suggests that these areas are highly productive potentially due to environmental factors which made them more resilient to overall fishing pressure. The Horns Reef Ground (indicated with a 4, Fig. 4) e.g. is situated in the upper part of the Elbe River Glacial Valley where the influx of Elbe river water causes a mini-upwelling in addition to an amphidromic point north of the area (Dyke 2007). Small beam trawls on the other hand mostly target shrimp and therefore do not exhibit the same problematic cocorrelation between high effort and high abundances of target fish species. Shrimp fishing concentrates in tidal channels with high current velocities (Schulte et al. 2015), not overlapping with high occurrences of adult target fish.

Overall, depth and habitat type were the most influential factor in explaining CSI values. For large beam trawls depth did not play a significant role because the two main fishing areas, the Dogger Bank (G) and North-western German Bight (D) are both similar in depth (between 30 to 46 m) which is the depth range where 95 % of total beam trawl effort is located. CSI values across the Dogger Bank are higher which coincides both with lower effort (average 0.3 SAR in G and 0.5 SAR in D), but also with the Dogger Bank being further offshore featuring a species (abundance) composition of more sensitive species (higher SIs).

While we were able to partition the variance into single components of pure trawling and pure environmental effects, causality was not so easy to infer. In certain highly fished areas

CSI values were still high, which does not mean that CSI increases with fishing pressure. The fact that fish communities in deeper waters contain more sensitive species simply concealed a clear relationship.

While we hypothesise that previous to industrial level fishing, CSI values would have been higher and have now potentially stabilised and adapted to chronic fishing pressure this can only be tested with historical data. We did not include any long-term temporal effects in this study. Hence, it is not possible to assess whether the pattern that we see today is first and foremost a result from decades if not a century of industrial fishing. Studies have shown that all long-lived, sensitive benthic species such as sea pens and *Sabellaria* reefs have been heavily depleted in the study area as a result of fishing (Holt et al. 1997). Likewise the fish community has changed over long time-frames in favour for fast growing and reproducing, smaller, short lived species that were able to cope better with additional fishing mortality (Daan 2006).

The well published change of the North Sea ecosystem during the 1980 coincided with highest fishing effort levels but also with climatic changes (Quante & Colijn 2016). Historic data exist at the ICES rectangle level and have been analysed by several authors in comparison to changes in fishing pressure for (parts) of the North Sea (Rijnsdorp et al. 1996; Greenstreet et al. 1999; Callaway et al. 2007) and the German Bight specifically (Fock et al. 2014). Studies have found a decrease in body size and abundance as well as in species diversity patterns. It is thus very likely that a change in the community structure has happened well before the onset of the GASEEZ monitoring used in this study. Our study adds to the recent literature describing similar challenges from chronically trawled areas (Pommer et al. 2016; Szostek et al. 2016; Farriols et al. 2017).

5. Conclusions

The CSI showed anticipated patterns for the small beam trawl fleet and in more coastal areas. This emphasises the importance of ecologically linking the indicator to a specific pressure. The monitoring of fish community state will become increasingly important as we move towards implementing ecosystem-based management and is therefore an important addition to the current focus on species-level indicators under descriptor 1 (biodiversity) of the MSFD. While the CSI proofed to be a valid surveillance indicator, its full operationalisation towards a pressure-state indicator for management requires carefully designed experimental studies on its responsiveness to fishing (e.g. using suitable reference areas). Potentially, Natura 2000 sites in which trawling will be restricted or banned may provide such areas in the future.

Currently, there are clear limitations to disentangle co-correlations between environmental effects, community compositions and fishing pressure. We therefore propose moving beyond pressure-state relationships towards holistic risk-based approaches (Stelzenmüller et al. 2015). In environmental risk assessments the link between pressure and state is not only accounted for as absolute relationships as it is in pressure-state assessments. Risk is assessed as a combination of the exposure likelihood of the state indicator with the pressure and the frequency, duration and impact rates of these encounters (Fock et al. 2011). As such real trade-offs can be uncovered and cumulative pressures analysed, including the influence of environmental drivers. This could help to assess consequences of management decisions under MSP on the good environmental status of ecosystem components managed under the MSFD. With this information potential EEZ-wide effects on the fish community can be examined and therefore aid decision-making to enable the integration of spatial management and conservation objectives.

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Supplementary information



Fig. S1. Depth–stratified scatterplots plots with a fitted loess smoother based on locally-weighted polynomial regression (red line) of grid cell values of the community sensitivity index (CSI) against the coefficient of range calculated from VMS data from 2010 to 2012 of the total trawling effort and for each fleet from the respective core fishing areas only.



Fig. S2. Results of CART analysis between CSI, total fishing effort, SBT and depth per Habitat type (A - H).



Fig. S3. Plots of GAM smoother describing the modelled relationship between the CSI and total trawling effort in SAR per habitat type after Rachor and Nehmer (2003) from the bivariate GAM analysis of the CSI explained by depth and total fishing effort [SAR] and GAM results; ED: explained deviance.



Fig. S4. GAM smoother and partial plots from univariate models [a, c, e] and the full model [b, d, f] describing the modelled relationship between the CSI, environmental variables and fleet-specific fishing pressure in the respective core fishing areas only (BTS: small beam trawls (< 221 kW); BTL: large beam trawls (> 221 kW); OBT: otter board trawls; SBT: sea bottom temperature; Habitat classiciation after Rachor and Nehmer (2003)). Core fishing areas were defined as fishing ground in which each fleet exerts more than 0.05 SAR and contributes at least 60 % of the total fishing effort per grid cell.

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Chapter 4

Quantitative environmental risk assessments in the context of marine spatial management: Current approaches and some perspectives

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Abstract

Marine spatial planning (MSP) requires spatially explicit environmental risk assessment (ERAs) frameworks with quantitative or probabilistic measures of risk, enabling an evaluation of spatial management scenarios. ERAs comprise the steps of risk identification, risk analysis and risk evaluation. A review of ERAs in in the context of spatial management revealed a synonymous use of the concepts of risk, vulnerability and impact, a need to account for uncertainty and a lack of a clear link between risk analysis and risk evaluation. In a case study we addressed some of the identified gaps and predicted the risk of changing the current state of benthic disturbance by bottom trawling due to future MSP measures in the German EEZ of the North Sea. We used a quantitative, dynamic and spatially explicit approach where we combined a Bayesian belief network (BN) with GIS to showcase the steps of risk characterisation, risk analysis and risk evaluation. We distinguished ten benthic communities and six international fishing fleets. The risk analysis produced spatially explicit estimates of benthic disturbance, which was computed as a ratio between relative local mortality by benthic trawling and the recovery potential after a trawl event. Results showed great differences in spatial patterns of benthic disturbance when accounting for different environmental impacts of the respective fleets. To illustrate a risk evaluation process, we simulated a spatial shift of the international effort of two beam trawl fleets, which are affected the most by future offshore wind development. The BN model was able to predict the proportion of the area where benthic disturbance likely increases. In conclusion, MSP processes should embed ERA frameworks which allow for the integration of multiple risk assessments and the quantification of related risks as well as uncertainties at a common spatial scale.

Key-words: Bayesian belief network, fishing frequency, GIS, marine spatial planning, review

1. Introduction

Place-based management tools such as marine spatial planning (MSP) are advocated worldwide to support the implementation of an ecosystem approach to marine management (Katsanevakis et al., 2011). In Europe, MSP is regarded as a means to solve inter-sectoral and cross-border conflicts over maritime space (Douvere and Ehler, 2010) and is promoted by the upcoming EU MSP Directive (Commission, 2014). The latter encourages blue growth and the sustainable use of marine resources (Qiu and Jones, 2013a; Brennan et al., 2014). One of the future challenges for European regional Seas is the alignment of the sustainable use of the marine resources with the maintenance of ecosystem health and functioning, as demanded by the EU Marine Strategy Framework Directive (MSFD) (Commission, 2008). Hence, an ecosystem based MSP process should seek to manage human activities while balancing multiple ecological, economic and social objectives (Foley et al., 2013).

As a consequence, an ecosystem based MSP approach requires robust estimates of the risks of adverse effects of cumulative human pressures on the marine environment at meaningful ecological scales (Eastwood et al., 2007; Halpern et al., 2008a; Stelzenmüller et al., 2010a; Fock et al., 2011b). Environmental risk assessments (ERAs) (Hope, 2006) that link spatially explicit information on the vulnerability of ecosystem components with the occurrence and magnitude of pressures are fundamental for the successful implementation of an ecosystem based MSP approach. The fast growing number of MSP initiatives (Carneiro, 2013; Collie et al., 2013) highlights the increasing importance of spatially explicit ERAs and underpins the need for quantitative or probabilistic measures of risk.

In general, quantitative risk assessments rely on mathematical models to predict the response of the ecosystem component to changing pressures. Qualitative approaches, however, use ecosystem attributes combined with ecological receptors and stressors (Astles et al., 2006). As for today, empirical studies on ERAs that provide, for example, spatially explicit quantifications of risk in relation to management options appear at a slower pace and take various risk assessment approaches (Stelzenmüller et al., 2010a; Fock et al., 2011b; Gimpel et al., 2013; Redfern et al., 2013). In the light of existing EU policies, in particular the MSFD and new MSP Directive, there is a growing need to align various spatially explicit ERAs to ongoing spatial management processes.

To account for this we adopted the risk assessment framework described in (Cormier et al., 2013) to first, assess current ERA approaches and second, structure a case study on the risk of

benthic disturbance in the German EEZ of the North Sea. The risk assessment framework comprises three steps. First, the risk identification specifies the pressure(s) of concern and the significant ecosystem components. Second, the risk analysis accounts for both, the probability and the magnitude of the pressure, its impacts on ecosystem components, and the degree of uncertainty involved. Third, the risk evaluation assesses the likely impacts on ecosystem components under alternative management measures.

We first reviewed empirical studies of spatially explicit and quantitative ERAs in the context of spatial management and assessed in detail the methods used for the risk identification, risk analysis and risk evaluation. To address some identified methodological gaps we defined a case study which describes the stepwise assessment of the risk when changing the current state of benthic disturbance by trawling due to future MSP measures in the German EEZ. Thus in the risk identification step we defined the offshore wind development and the related displacement of fishing effort as pressures. We identified ten benthic communities as described by (Rachor and Nehmer, 2003) as an example of significant ecosystem components since the good environmental status of seabed integrity reflects one of the goals of the MSFD. In the risk analysis step we computed spatial estimates of a benthic disturbance indicator (Fock, 2011a), which was defined as a ratio between relative local mortality by demersal trawling fleets and recovery potential of benthic communities (see (Hiddink et al., 2006b).

For the risk evaluation we used a spatially explicit probabilistic approach that allows a dynamic assessment of possible trade-offs of alternative spatial management scenarios. We coupled a Bayesian belief network (BN) with GIS and predicted occurrence probabilities of different states of benthic disturbance and % changes of the study area in relation to simulated spatial management objectives. BNs are acyclic graphs that represent causal dependencies among a set of random variables by means of directed links between them (McCann et al., 2006). Recently, they have been used in combination with GIS to conduct a spatially explicit assessment of the risk involved with spatial management options (Fock et al., 2011a; Johnson et al., 2012; Grêt-Regamey et al., 2013a; Grêt-Regamey et al., 2013b). In summary, here we identified some shortcomings of current spatially explicit ERA approaches, and showed some perspectives for assessing trade-offs of MSP scenarios in the German EEZ of the North Sea. Finally, we reflected on the challenges ahead when it comes to the integration of numerous assessment outputs in a multiple objectives spatial management context.

2. Material and methods

2.1 Risk assessment framework and review of current approaches

We adopted the standardised risk assessment framework defined by (Cormier et al., 2013) to frame the steps of risk identification, risk analysis and risk evaluation in a spatial management context (Fig. 1). We then analysed recent empirical studies of (semi-) quantitative environmental risk assessments in the context of marine spatial management with regard to these key steps. Here spatial management was rather broadly defined and encompassed studies concerned with MSP, sectoral management or marine conservation. With the help of multiple combinations of the key words: environmental risk assessment, risk analysis, quantitative, vulnerability, spatial management, marine spatial planning, and map(ping) we selected a total of 32 peer-reviewed papers. In the following we describe the three risk assessment steps in more detail and specify what information has been extracted from the reviewed literature.



Fig. 1. Simplified risk management process redrawn from (Cormier and al., 2013) in the context of marine spatial management such as MSP. Spatial management goals and operational objectives (Stelzenmüller et al., 2013) determine the contents of the environmental risk assessment. Risk assessment results enter the risk treatment phase which produces management options, based on costbenefit analysis of implementation. Suggested management options will in turn feedback in to the spatial management process (development, implementation or evaluation process).

Risk identification - The risk identification comprises the definition of significant ecosystem components, stressors or pressures as well as the related environmental cause-effect pathways defined by the operational management objectives for a given area. Operational objectives have specific, measureable, achievable, realistic and time limited (SMART) targets, such that management measures can be fitted and performance can be evaluated (Stelzenmüller et al., 2013). Stressors are single or multiple human pressures while cumulative impacts are described as the combined impact of multiple pressures over space and time (MacDonald, 2000). Here risk identification comprises also an estimate of the occurrence probability and magnitude of the pressure and the spatial quantification of the identified ecosystem components or state indicator. According to this definition, the assessed pressures and ecosystem components or state indicators together with the methods used to quantify their occurrence in the respective area were extracted from the reviewed empirical studies.

Risk analysis - This step addresses the quantification of impacts on ecosystem components that accounts for existing mitigation or management measures as well as the risk acceptance in society. The latter should be reflected in the operational management objectives. The impact is generally defined as a function of the vulnerability of ecosystem components and the occurrence likelihood and magnitude of a pressure (Stelzenmüller et al., 2010a). (De Lange et al., 2010) proposed to define vulnerability of an ecosystem component by means of exposure and sensitivity to a pressure as well as its recovery potential. The sensitivity to a pressure is due to structural properties, functions or trophic relations of the ecosystem component while recovery depends on population recovery, resilience, positive feedback loops and adaption (Tyler-Walters et al., 2001; Hope, 2006; Halpern et al., 2008b). We classified each case study according to the type of sensitivity measure used (expert knowledge, model output, empirical data) and the vulnerability assessment approach applied. Uncertainty should be recognised and constructively handled for any integrated risk assessment or models based decision support (Rotmans and van Asselt, 2001). For instance a recent review by (Ferdous et al., 2013) assessed methods which allow recognising and evaluating the implications of uncertainty in a risk analysis. Thus we reported further if any form of uncertainty analysis was undertaken and which methods have been used.

Risk evaluation - The result of a risk evaluation indicates whether or not new management actions need to be taken. Technically, this requires the evaluation of management scenarios, including the "the business as usual" scenario. More precisely, it entails a comprehensive assessment of the proposed management measures and scenarios with respect to the potential

risks for relevant ecosystem components. Thus we investigated what kind of management scenarios, if at all, have been tested in the empirical studies.

2.2 Case study area and context

The here described risk assessment framework has been hardly applied to marine ecosystems in all aspects. We thus designed a case study assessing future MSP measures in the German EEZ and their likely implications for benthic communities using a quantitative, dynamic and spatially explicit approach. Since 2008 the maritime spatial plan is legally binding in the German EEZ and comprises designated preference areas for a number of sectors except fishing, including special areas of conservation designated under the Habitat Directive (92/43/EEC, 1992); Natura 2000 sites (BMVBS, 2009) (Fock, 2011b; Fock et al., 2011a; Gimpel et al., 2013). Further environmental objectives with potential spatial management measures are defined by the MSFD and require implementation by 2020. For illustration purposes we simplified this rather complex spatial management context and focused only on seabed integrity and defined the hypothetical operational management objective "The relative benthic disturbance by trawling should not deteriorate with respect to current levels". This operational objective defines the impact of trawling on benthic communities as the measure or indicator of concern and specifies the current level as the reference point. Therefore future MSP measures, which comprise the designation of offshore wind development sites within approx. 35 % of the study area, will be assessed against the here defined management objective. Future offshore wind development sites in the German EEZ show a clear spatial overlap with prevailing patterns of fishing (Fock et al., 2011a). Thus the potential area loss for fishing will most likely result in an effort displacement with as yet unknown environmental and economic consequences. In the following we describe the risk assessment steps for the current case study.

Risk identification - Offshore wind development, fisheries and benthic communities

We considered the currently designated offshore wind development sites as MSP measures as well as the submitted application areas. The development of this sector triggers a number of conflicts with other human uses through the competition for the same space (Gimpel et al., 2013). The highest conflict potential can be expected between the (international) fishing sector and the offshore wind development, since e.g. roughly 15 % of the total international large beam trawl effort takes place in areas where offshore wind development is envisaged. Thus we defined the average spatial and temporal activity of six different fishing fleets as

pressures following (Fock, 2011a) and (Fock et al., 2011a) regarding to seabed integrity (as specified above). For this we combined German, Dutch and Danish VMS (vessel monitoring system) and logbook data from 2005 to 2008 to calculate the average bottom trawling effort (total hours fishing per year) per 3 x 3 nm grid cell (31 km²). We distinguished six different fleets, which are beam trawlers operating with 80 mm mesh size and an engine power > 221KW (Beam80lrg) and < 221 KW (Beam80sml), beam trawler with 16 to 31 mm mesh size and an engine power > 221 KW (Beam1631lrg) and < 221 KW (Beam1631sml), and otter trawlers with 80 mm mesh size and an engine power > 221 KW (Otter80lrg) and < 221KW (Otter1631sml). For each grid cell we computed the frequency with which the seabed surface has been swept by the respective fleet (Ffrik) using the formula and parameters also presented in (Fock, 2011a) ($Ffr_{ik} = \frac{T_{ik}*V_k*w_k}{A_i}$; with T_{ik} =total hours fished (h), V_k = average fishing speed (km/h), w_k = net spread (km), and A_i = surface area in km²). The ecosystem components of concern were ten benthic communities with a defined spatial distribution (Figure 2) and specific characteristics such as habitat preference or recovery frequency (Table 1) (Rachor and Nehmer, 2003; Pesch et al., 2008; Fock, 2011a). Thus with the help of GIS we allocated to each grid cell the most dominant benthic community with respective measures of recovery potential and mortality rates (see below) together with the average fishing frequency per fleet.



Fig. 2. Predicted spatial distribution of the infaunal benthic community in the German EEZ of the North Sea and adjacent waters (redrawn after Pesch et al., 2008).

Risk analysis – Measuring benthic disturbance

The next step required the definition of vulnerability of the ecosystem components to fishing pressures exerted by the different fleets. We built on a previous study (Fock, 2011a) and references therein) and computed spatial estimates of the disturbance indicator (DI). DI_i reflects an overall relative local vulnerability of a benthic community to bottom trawling and is defined as the ratio between mortality and recovery (M_i/R_i). DI_i is a unitless relative ratio and $DI_i = 1$ indicates a balance between relative local mortality and recovery. $DI_i > 1$ indicates locally higher mortality rates than recovery potential, whereas $DI_i < 1$ indicates that the recovery potential exceeds local mortality rates by trawling.

The computation of this ratio requires relative estimates of recovery time and recovery frequency for each of the ten benthic communities (see Table 1). We used the proportion of typical sediment categories (mud, sand, muddy sand, and gravel) favoured by the respective benthic communities (Rachor and Nehmer, 2003) to construct combined relative measures of recovery time (y) ($RT_{BC} = \sum R_{Sediment} \cdot Proportion$ sediment) and recover frequency (y⁻¹) $(Rfr_{BC} = \sum Rfr_{Sediment} \cdot Proportion sediment)$, both in relation to one trawling event. With this we computed for each grid cell the relative recovery for each benthic community to 90 % of the abundance previous to trawling as a function of the recovery time and recover frequency $R_i = 1 - (1 - 0.9 \cdot RT_{BC})^{RfrBC}$ (Fock, 2011a). Hence, the here applied measure of sensitivity to benthic trawling is derived from model outputs presented in Hiddink et al., (2006b) and empirical results by Rachor and Nehmer (2003). In a next step, we computed for each grid cell the local mortality rate for each benthic community. For this we used the average percentage decline of abundance per sediment type (taken from Fock, 2011a) to construct an average combined measure of mortality per benthic community (MR_{BC} = \sum Decline_{Sediment} Proportion sediment) (see Table 1). Accordingly, we computed for each grid cell the fleet specific mortality rate for the benthic community as $M_{ik} = 1 - (1 - MR_{BC})^{Ffrik}$. The overall local mortality rate is the sum of these mortality rates weighted by a respective impact sore (*is*); $M_i = \sum_{k=1}^n M_{ik} * is_k$ (modified after Fock, 2011a). This finally allowed us to compute the ratio between relative local mortality and recovery (M_i/R_i) , and we refer to this as disturbance indicator (DI_i). We further explored the uncertainty within the estimates of benthic disturbance by accounting for fleet specific impacts on benthic communities. For that reason we calculated DI_i based on a local overall mortality rate (M_i) by assuming equal impacts of each fleet (i.e. impact score $is_k = 1$). Alternatively, we computed DI_{iw} with a local overall mortality rate weighted by different impact scores (adapted from Fock, 2011a).

Here highest weight is given to the beam trawlers operating with a mesh size of >80 mm, which represent mainly the fishery targeting flatfish, and least weight is given to the small beam trawlers using mesh sizes of 16-31 mm, representing the shrimp fishery ($is_{BEAM80lrg} = 1$; $is_{BEAM80sml} = 1$; $is_{BEAM1631lrg} = 0.1$; $is_{BEAM1631sml} = 0.1$; $is_{OTTER80lrg} = 0.15$; $is_{OTTER80sml} = 0.15$). We compiled for each grid cell the respective measures of recovery, mortality and benthic disturbance in ArcGIS 10.0 using the attribute table of the vector grid for subsequent mapping. Thus, DI and DI_w describe spatially disaggregated alternative assumptions of the relative state of benthic disturbance, based on the average bottom trawling effort from 2005-2008.

Table 1. Ten benthic communities as defined by Rachor and Nehmer (2003) comprising Amphiura filiformis 89% (AF); Bathyporeia fabulina 85%, Amphiura filiformis 10% (BtAf); central North Sea (cNS); Tabulina fabula (Tf) 83%, Goniadella spisula (GS) 12,5% (Tf0.83GS0.13); GS30%, Tf30%, Macoma balthica (Mb) 20%, Nucula nitidosa (Nn) 10% (GS0.3Tf0.3Mb0.2Nn0.1); GS 100% (GS1.0); GS 93% (GS0.93); Helgoland depth 75%, Nn 25% (Helgoland0.75Nn0.25); Mb 100% (Mb); Nn 84% (Nn).

Benthic community	AF	BtAf	cNS	Tf0.83	GS0.3Tf0.3	GS1.(GS0.	Helgoland	Mb	Nn
				GS0.13	Mb0.2Nn0.1		93	0.75Nn0.25		
Prop mud ⁺					0.11			0.8		0.84
Prop muddy sand ⁺	1	0.15	0.5		0.28					0.16
Prop sand ⁺		0.85	0.5	0.93	0.44	0.5	0.6	0.15	0.50	
Prop gravel ⁺				0.07	0.16	0.5	0.4	0.05	0.50	
R _{Mud} (days)	25	25	25	25	25	25	25	25		
R _{MuddySand} (days)	111	111	111	111	111	111	111	111	111	111
R _{Sand} (days)	193	193	193	193	193	193	193	193	193	193
$\operatorname{Rfr}_{\operatorname{Mud}}(\operatorname{y}^{-1})$	14	14	14	14	14	14	14	14	14	14
$\operatorname{Rfr}_{\operatorname{MuddySand}}(y^{-1})$	3	3	3	3	3	3	3	3	3	3
$\operatorname{Rfr}_{\operatorname{Sand}}(y^{-1})$	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
$Rfr_{Gravel}(y^{-1})$	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Decline _{Mud} (prop)	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345
Decline _{MuddySand} (prop)0.675	0.675	0.675	0.675	0.675	0.675	0.675	0.675	0.675	0.675
Decline _{Sand} (prop)	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535
Decline _{Gravel} (prop)	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74
$RT_{BC}(y)$	0.3	0.5	0.42	0.49	0.33	0.26	0.32	0.13	0.26	0.11
$\operatorname{Rfr}_{\operatorname{BC}}(\operatorname{y}^{-1})$	3	1.73	2.25	1.4	3.06	0.8	0.94	11.5	0.8	12.24
R _{BC}	0.62	0.64	0.65	0.56	0.65	0.2	0.27	0.77	0.2	0.71
MR _{BC} (proportion)	0.68	0.56	0.61	0.55	0.58	0.64	0.62	0.39	0.64	0.40

^aThe proportion of sediment per benthic community has been derived from Fock (2011a) based on a study from Rachor and Nehmer (2003). For each community the relative distribution on four different sediment types, their sediment specific recovery time (R), recover frequency (Rfr), and decline after one trawling event (Decline) is given (after Fock, 2011a; Hiddink et al., 2006a). Further, the community-specific combined values are listed as relative combined recovery time (RTBC), the relative combined recover frequency (RfrBC), the relative combined recover frequency (MRBC).
Risk evaluation – Trade-off analysis of MSP measures

This final step corresponds to the evaluation of the risk of worsening the current state of benthic disturbance due to future MSP measures in the German EEZ. Our scenario applies to planned offshore wind development sites, where, in case of their realisation, extensive areas would be closed for fishery. As a rough estimate 15% of the large beam trawl effort and 3% of the small beam trawl effort would be affected. Effects on the fleets using otter boards are negligible. Thus, we defined the following spatial management scenario: "*Current and future offshore wind development cause a spatial shift of 15 % of the total fishing frequency of large beam trawlers (Beam80lrg) and 3% of the small beam trawlers (Beam1631sml)"*. We combined a Bayesian belief network (BN) with GIS to predict changing likelihoods of benthic disturbance states due to different trawling effort patterns. We used the Netica software system (www.norsys.com) (see details on the inference algorithm implemented in Netica in Spiegelhalter and Dawid (1993) to develop the BN model and used the attribute table compiled in the GIS to both built the prior probabilities for each variable (referred to as BN node) and to populate the conditional probability tables (CPTs) (see Table 2).

The BN model contains the deterministic relationships described above and reflects the causal links of all parameters required to calculate the unweighted and weighted disturbance indicator (Fig. 3). Benthic communities and the fishing frequencies of the six fleets are parent nodes and are considered to be independent from each other. Each parent node has discrete states (e.g. type of benthic community, category of fishing frequency) with an associated probability of occurrence. Fleet specific mortality rates are represented as functions of the respective fishing frequencies and the estimated decline rates for each benthic community. The overall mortality rate and weighted mortality rate are child nodes of the fleet specific mortality rates and are defined by their deterministic relationships with their parent nodes. Recover frequency, recovery time, and abundance decline are child nodes of the benthic communities. The likelihoods of the states of the disturbance indicator nodes are predicted as a function of the likelihood of the overall relative mortality rates (unweighted and weighted) and the predicted recovery by the benthic community.

We also assessed the sensitivity of the disturbance indictor node (DI) to the influence of the parent nodes by calculating the variance reduction. The performance or "goodness of fit" of the BN model was tested by computing the spherical payoff index (see Marcot et al., 2006a).

The latter describes how well the predictions of the BN match the actual cases and is defined as the mean probability value of a given state averaged over all cases.

Subsequently, we explored the effects of the planned offshore wind development sites on the two measures of benthic disturbance (DI and DI_w) with the help of the trained BN. We assumed that in 15 % of the area the likelihood of experiencing the lowest level of fishing pressures by large beam trawlers will increase (since 15 % of the area will be closed for this fisheries). Assuming that the fishing effort will relocate in areas with already high fishing intensity, the probability of a unit area experiencing the highest level of fishing pressures (or being in state 3) must increase. Thus we changed in the BN model the prior distribution for the Beam80lrg node, with now 47 % of the area having a value from 0 to 0.0025 and in 53 % of the area values range between 0.06 and 1.16. We inferred subsequently the changes of the probability distributions of the DI and DI_w nodes. Based on the same rational we have changed the prior distribution for the Beam1631sml node assuming that in 66 % the area no fishing is carried out by this fleet, while in 12 % of the area values range between >0 and 0.07, and in 22 % of the area values range between <0.07 and 1.17. It is worth mentioning that the here defined spatial shift in fishing effort reflects one out of many possible changes to the prior distributions of the parent nodes reflecting the fishing frequencies of the six fleets.

Table 2 Description of RN model nodes	discretisation method and states. Not	te· Δ11 model nodes reflect att	ributes from the 3 by 3 nm ve	ctor grid
Table 2. Description of Divinouer nodes,	discretisation method and states. 100	ic. The model nodes reflect an	The short the story shift ve	cior griu.

BN node	States	Description
Recover_frequency_BC	0-1.4; >1.4-3; >3-12.24	Relative combined recover frequency for each benthic community (y^{-1}) (Table 1; Rfr _{BC} = $\sum Rfr_{Sediment}$.
		Proportion sediment) from benthic trawling.
Recovery_time_BC	0-0.26; >0.26-0.33; >0.33-0.5	Relative combined recovery time for each benthic community (y) (Table 1; $RT_{BC} = \sum R_{Sediment}$.
		Proportion sediment) from benthic trawling.
Abundance_decline_BC	0-0.5; >0.5-0.58; >0.58-0.68	Relative combined abundance decline after one trawling event for each benthic community (Table 1;
		$MR_{BC} = \sum Decline_{Sediment}$ ·Proportion sediment)
Recovery	0-0.56; >0.56-0.62; >0.62-0.78	Relative local recovery rate for each benthic community (Table 1; $R_i = 1 - (1 - 0.9 \cdot RT_{BC})^{RtrBC}$)
FrBeam80LR	0-0.0025; >0.0025-0.06; >0.06-1.16	Fleet specific mean (2005 to 2008) fishing frequency ($Ffr_{ik} = \frac{T_{ik} * V_k * w_k}{T_{ik}}$; with T_{ik} =total hours fished (h),
FrBeam80SM	0; >0-0.0004; >0.00004-0.076	V_{i} = average fishing speed (km/h) w_{i} = pet spread (km) and A_{i} = surface area in km ²) with which the
FrBeam1631LR	0; >0-0.00019; >0.000019-0.000347	v_k – average fishing speed (kii/i), w_k – liet spread (kii/), and AI– surface area in kiii) with which the
FrBeam1631SM	0; >0-0.07; >0.07-1.17	surface area has been swept (Beam – beam trawlets, Otter – otter board trawlets, $\delta 0 = \delta 0$ min mesh size, 1621 – 16 to 21 mm mesh size, LP – orgina power > 221KW, SM – orgina power < 221KW)
FrOtter80LR	0; >0-0.000279; >0.000279-0.335	1051 - 1010 51 minimissi size, LK – engine power > 221Kw, SW – engine power < 221Kw).
FrOtter80SM	0-0.0007; >0.0007-0.012; >0.012-	
	0.524	
M_Beam80LR	0-0.0021; >0.0021-0.05; >0.05-0.45	Fleet specific relative mean mortality rates of the prevailing benthic community as a function of the
M_Beam80SM	0; >0-0.0007; >0.0007-0.058.	mean frequency of the respective fleet and the combined average abundance decline rate ($M_{ik} = 1 - (1 - 1)$
M_Beam1631LR	0; >0-0.000134; >0.000134-0.00039.	MR_{BC}) ^{rink} (Beam = beam trawlers, Otter = otter board trawlers, 80 = 80 mm mesh size, 1631 = 16 to 31
M_Beam1631SM	0; >0-0.06; >0.06-0.64	mm mesh size, $LR = engine power > 221KW$, $SM = engine power < 221KW$) (see Table 1).
M_Otter80LR	0; >0-0.000313; >0.000313-0.31	
M_Otter80SM	0; >0-0.000313; >0.000313-0.31	
Mortality_rate	0-0.032; >0.032-0.14; >0.14-0.84	Overall mean local mortality rate expressed as the sum of the mean local mortality rates per fleet (from
		2005 to 2008) weighted by equal impact scores (is): $M_i = \sum_{k=1}^{n} M_{ik} * is_k$; $is_k = 1$
Mortality_rate_W	0-0.032; >0.032-0.14; >0.14-0.84	Overall mean local mortality rate weighted by different impact scores (<i>is</i>): $is_{BEAM80lrg} = 1$; $is_{BEAM80sml} = 1$;
		$is_{BEAM1631lrg} = 0.1$; $is_{BEAM1631sml} = 0.1$; $is_{OTTER80lrg} = 0.15$; $is_{OTTER80sml} = 0.15$
Disturbance_indicator	0-0.3; >0.3-0.5; >0.5-1; >1-3	Estimated disturbance indicator (DI _i) as the ratio between mortality rate and recovery.
Disturbance_indicator_W	0-0.3; >0.3-0.5; >0.5-1;>1-3	Estimated disturbance indicator (DI _{iW}) as the ratio between the weighted mortality rate and recovery.
Benthic_communities	AF; BtAf; cNS; Tf0.83GS0.13;	Ten categories of benthic communities as defined by (Rachor and Nehmer, 2003) comprising Amphiura
	GS0.3Tf0.3Mb0.2Nn0.1; GS1.0;	filiformis 89% (AF); Bathyporeia fabulina (85%), Amphiura filiformis (10%) (BfAf); central North Sea
	GS0.93; Helgoland0.75Nn0.25; Mb;	(cNS); Tabulina fabula (83%), Goniadella spisula (12,5%) (Tf0.83GS0.13); Goniadella spisula (30%),
	Nn	Tabulina fabula (30%), Macoma balthica (20%), Nucula nitidosa (10%) (GS0.3Tf0.3Mb0.2Nn0.1);
		Goniadella spisula (100%) (GS1.0); Goniadella spisula (93%) (GS0.93); Helgoland Depth 75%, Nucula
		nitidosa (25%) (Helgoland0.75Nn0.25); Macoma balthica (100%) (Mb); Nucula nitidosa (84%) (Nn)



Fig. 3. Structure of the Bayesian belief network for assessing future MSP measures in the German EEZ and their likely implications for benthic communities. Values for categorical probabilities (%) of each node are given for the baseline scenario (referred to as "business as usual scenario") (node definitions in Table 2).

3. Results

3.1 Review of current approaches

The results of the structured literature review of 32 papers are summarised in Table 3. Most studies focused on one or two stressors with a clear emphasis on fisheries; other activities included aggregate mining and marine traffic. Cumulative pressures were analysed in a quarter of all examined studies, mostly assuming additive effects. We observed that the measure of sensitivity of ecosystem components or indicators was mostly related to a metric derived from a model output which based either on empirical data or expert knowledge. In contrast, a quarter of the reviewed studies were based on expert knowledge and three studies being based exclusively on empirical data. Another important result was that the terminology of risk, vulnerability and impact varied greatly across the studies and has been used synonymously. Despite this variation in terminology the components to calculate a measure of vulnerability or impact have been similar across all cases. All studies defined vulnerability or impact as a function of a measure of ecosystem sensitivity and the occurrence probability and magnitude of a stressor or pressure. However, the concepts of resistance and resilience of ecosystem components were only considered in a few studies. The dominating type of assessment outputs (13 studies) have been maps with 'semi-quantitative measures per unit areas' (from 250 m² to 90 km²), followed by 'quantitative measures per unit area' (from 400 m to 100 km²) in 12 studies, only a small proportion of the assessment outputs related to quantitative (2 studies) or semi-quantitative (5 studies) measures for given management units (thus one value for a case study area). More than half of the reviewed studies carried out a risk evaluation and tested a broad range of scenarios including simulated pressure-effect scenarios, mostly related to the future license areas of wind farms or fisheries management measures. Cumulative effect scenarios have been tested by weighting for instance the relationship between indicators and pressures. It is relevant to allude to the fact that about one third of the studies did not account for uncertainty. Some studies assessed uncertainty quantitatively based on model uncertainty. Other studies addressed uncertainty in a qualitative way, mainly by a discussion about the issue of uncertainty and/or proposed methods for further analysis.

Table 3. List of 32 recent empirical studies of (semi-) quantitative environmental risk assessments in the context of the development, implementation or evaluation of marine spatial management. Studies were reviewed according to the spatial scale and the methods with regard to the three steps of a risk assessment: risk identification, risk analysis and risk evaluation.

Scale and location	Risk identification and char	acterisation	Risk analysis	3		Risk evaluation	References
small <500.000km ² meso >=500.000-106 km ² , large >=106km ²	Stressor(driver)/pressure indicators used	Ecosystem components/ state indicators	Measure of sensitivity of state indicators	Measure and approach used of vulnerability/risk/impact of ecosystem/ area	Assessment output type	Management scenario analysis (assessed: yes/no)	
Small (ca. 270.000km ²); Great Barrier Reef MPAs, Australia	Pollution	Mulitple habitats (coral reefs and seagrass beds)	Model output	Frequency of plume occurrence with spatially distributed loads; final maps of exposure (E) = annual frequency of plume occurrence grid (F)*sum of spatially distributed TSS and DIN loads grid [for all rivers (P)]	Quantitative measures per unit area; mapping out approach of frequencies	No	(Alvarez- Romero et al., 2013)
Small; 3 Italian MPA, Mediterranean Sea	Multiple human and environmental stressors	Multiple habitats	Empirical data, expert knowledge	Environmental diagnostic = \sum scores of individual habitat per cell for degradation and risk [level]; weighted vulnerability [vulnerability of habitat*number of cells where the habitat is present]; environmental quality [\sum naturalistic*economic*aesthetic*rarity of the habitat]; susceptibility to human use [number of habitats*importance]	Semi-quantitative measure per unit area; mapping out approach of environmental quality, susceptibility to use, weighted vulnerability	No	(Bianchi et al., 2012)
Meso (ca. 500.000km²); Canada's EEZ, Pacific coast	Cumulative pressure (additive) from human stressors	Multiple habitats	Expert knowledge	Cumulative impact = $\sum(intensity*habitat*vulnerability (vulnerability score for activity i and habitat j, by expert judgement), MPA restrictions included$	Quantitative measure per unit area (400m grid); cumulative impact score matrices	Yes, three scenarios were used:1) include each fishery separately, 2) summarize fisheries by type of impact, 3) include only one layer for commercial and one for recreational fisheries	(Ban et al., 2010)

Scale and location	Risk identification and char	acterisation	Risk analysis	5		Risk evaluation	References
Large; Australasia	Cumulative pressure (additive, antagonistic, synergistic) from global (climate change) and local (nutrient input) stressors	Habitat (seagrass)	Empirical data	Additive effects model (effect size*stressor values) to test for interactions between pressures (no, antagonistic and synergistic interactions)	Quantitative measure per unit area (100km ²); interactive impact maps (local and global stressors)	Yes, the management effect of each pressure has been assessed	(Brown et al., 2013)
Small (ca. 70km²); Ebro Delta, NW Mediterranean Sea	Offshore windfarms	Multiple species (sea birds)	Empirical data, model output	Potential risk = spatial overlap between aggregative patterns of seabirds [coupling Taylor's power law (TPL) with linear mixed effect models] and offshore wind farm placement	Semi-quantitative measure per unit area (12.5km ²); mapping out approach risk	Yes, future offshore wind farm areas have been considered	(Christel et al., 2013)
Small; South Florida coastal ecosystem, Gulf of Mexico	Multiple global (e.g. climate change) and local (e.g. fishing) stressors	Multiple species, multiple habitats	Expert knowledge	Impact = matrix-based analyses of pressures to states and services, scored by expert opinion	Quantitative measures for given management unit; relative impact matrices	No	(Cook et al., 2013)
Small (28.500km²); German EEZ, North Sea	Fisheries	Habitat (benthic)	Model output	Risk = proportion of the ecosystem component* \sum (proportion of the cell*gain function per cell (\sum recovery potential over mortality potential for all impacts))	Quantitative measure per unit area; distribution of cumulative risk by area and benthic distribution	Yes, four scenarios evaluated against goals from European maritime policies (MSFD, CFP, HD)	(Fock et al., 2011b)
Small (28.500km²); German EEZ, North Sea	Fisheries, aggregate extraction	Multiple species (benthic, mammals, sea birds)	Model output	Loss and exposure = mortality (M) / recovery (R)	Quantitative measure per unit area (3*3nm/6*6nm); risk scores by area and ecosystem function	No	(Fock, 2011a)
Small (256.500km ² and 40km ²); UK (English and Welsh) waters	Cumulative pressures (additive, antagonistic, synergistic) from fisheries and aggregate extraction	Multiple habitats (benthic)	Expert knowledge, model output	Cumulative impact = degree of disturbance from type of fishing gear, fishing intensity, habitat sensitivity and recovery rates	Quantitative measure per unit area (1km²); cumulative impact scenario output	Yes, four cumulative effects scenarios (greatest, additive, antagonistic and synergistic) to estimate overall recovery times	(Foden et al., 2010)

Scale and location	Risk identification and char	acterisation	Risk analysis	5		Risk evaluation	References
Small (256.500km ²); UK (English and Welsh) waters	Cumulative pressures (greatest, additive, antagonistic, synergistic) from human stressors	Multiple habitats (benthic)	Expert knowledge, model output	Cumulative impact = degree of disturbance from type of pressure, pressure intensity, habitat sensitivity and recovery rates	Quantitative measure per unit area (1km ²); cumulative impact scenario output	Yes, four cumulative effects scenarios (greatest, additive, antagonistic and synergistic) to estimate overall recovery times	(Foden et al., 2011)
Small (ca. 55.500km ²); Northern- Central Adriatic, Mediterranean Sea	Fisheries	Multiple species (functional groups)	Model output	Biomass and catch changes = amount of total biomass, commercial species biomass, predator species biomass, fish biomass, invertebrates (except plankton) biomass, total catch, demersal catch, pelagic catch) assessed using spatial- temporal food web model Ecospace	Quantitative measure per unit area (25km ²); scenario output tables	Yes, scenarios regarding spatial management (MPAs), three temporal simulations of temporary closures and overall reduction of fishing effort (Ecospace)	(Fouzai et al., 2012)
Small, Scottish waters	Cumulative pressures (additive) from human stressors	Multiple species (sea birds)	Expert knowledge, model output	Disturbance risk = (ship and helicopter traffic, habitat specialisation)*conservation importance	Semi-quantitative measure for given management unit; ranked species concern scores	No	(Furness and Tasker, 2000)
Small (28.500km²); German EEZ, North Sea	Cumulative pressure (additive) from human stressors	Single species (fish)	Expert knowledge, model output	Risk = pressure to state vulnerability [severity and duration of (negative) effects (due to human pressure) + the sensitivity of species (resiliency, reversibility, sensitivity etc.)]	Semi-quantitative measure per unit area (5km²); mapping out approach and scenario output	Yes, multiple risk scenarios based on the identification of potential conflict areas between drivers and between pressures and nursery grounds	(Gimpel et al., 2013)
Small; coastal zone of the Great Australian Bight, South Australia	Fisheries	Multiple species (mammals)	Expert knowledge, model output	Risk of extinction = population viability analysis based on time and probability of terminal extinction and quasi extinction by subpopulation, region and marine fishing areas with the greatest bycatch risk	Semi-quantitative measure per unit area (10*10 km nodes); risk scenario output, bycatch rates	Yes, three scenarios of increasing, stable and decreasing population trajectories	(Goldsworthy and Page, 2007)

Scale and location	Risk identification and char	acterisation	Risk analysis			Risk evaluation	References
Small (ca. 26.000km ²); Great Barrier Reef, Australia	Cumulative pressure (additive) from human stressors	Habitat (seagrass)	Expert knowledge	Cumulative impact = vulnerability [frequency, functional impact, resistance, recovery time (years) and certainty]	Semi-quantitative measure per unit area (2km ²); cumulative impact score mapping	No	(Grech et al., 2011)
Small; Barcelona Habour, Spain	Pollution	Habitat quality (water)	Model output	Risk index = probability, exposure and vulnerability; branch-decision scheme to evaluate the cost of each decision as a function of vulnerability, proximity and toxicity of potential contaminants	Semi-quantitative measures per unit area; spatial distribution of risk	Yes, decision branch model based on cost/utility	(Grifoll et al., 2010)
Small, (125.000km ²); North Sea	Fisheries	Multiple species (benthic)	Model output	Relative ecological impacts of disturbance = degree to which production and biomass in habitats respond to trawling disturbance; sensitivity = recovery time	Semi-quantitative measures per unit area (9 km ²); impact maps	Yes, five management scenarios based on modelled reduction in biomass and production	(Hiddink et al., 2007)
Small (ca. 80.000km ²); Baltic Sea	Cumulative pressure (additive) from human stressors	Multiple habitats (benthic)	Expert knowledge	Cumulative impact = weighting of pressures to habitat specific impacts [statistical approach, thresholds based on mean \pm sd of cumulative impact within habitat type] using HELCOM weighting factors	Semi-quantitative measure per unit area (71289m²); cumulative impact scores	No	(Korpinen et al., 2013)
Small (1km²); Spanish coast, local beaches, Mediterranean Sea	Multiple human and environmental stressors	Habitat quality, multiple species, ecosystem function and services	Empirical data, expert knowledge	Risk = \sum hazard intensity*ecosystem service values [habitat, disturbance regulation, water supply, recreational and aesthetic services, spiritual and historic values]	Semi-quantitative measure for given management unit; risk valuation and prioritization	No	(Lozoya et al., 2011)
Small (20.000km ²); Brazilian coast (continental shelf area), Atlantic	Marine traffic, hydrocarbon exploration	Single species (mammals)	Empirical data, expert knowledge	Risk = humpback whale density category + anthropogenic impact category	Semi-quantitative measure per unit area (ca. 50km radius); risk mapping and conservation prioritization	No	(Martins et al., 2013)
Small (30km ²); Archipelago of La Maddalena (Sardinia, Italy), Mediterranean Sea	Pollution	Habitat quality (beaches)	Empirical data, expert knowledge	Risk = hazard index [normalised oil particle concentration derived from models]*vulnerability [geomorphology and environmental protection]	Semi-quantitative measure per unit area (90km ²); mapping out of hazard index	No	(Olita et al., 2012)

Scale and location	Risk identification and char	racterisation	Risk analysis	\$		Risk evaluation	References
Small (4km ²); Ligurian Sea MPA (Italy), Mediterranean Sea	Multiple human stressors	Multiple habitats	Expert knowledge, model output	Marine territory score (impact) = relationship between pressure intensities and ecosystem status (spatially resolved [distance of habitats from reference/unperturbed conditions (4 habitat indices)] and average over territory)	Semi-quantitative per unit area (250m ²): mapping of change in marine territory status (impact)	Yes, management scenarios based on experts judgment of changes in pressure intensities used in the model	(Parravicini et al., 2012)
Small (10.000km ²); Bay of BiscaySpanish EEZ at the Basque Coast, Atlantic	Fisheries	Multiple species (trophic levels)	Empirical data, expert knowledge	Total fishing pressure (TFP) = cumulative fishing intensity; fishing pressure per commercially relevant species; fishing pressure by trophic level	Semi-quantitative measure per unit area (1km ²); TFP maps	No	(Pascual et al., 2013)
Small (1km ²); San Foca tourist harbour (Italy), Mediterranean Sea	Pollution	Habitat quality	Expert knowledge, model output	Risk = likelihood of negative environmental changes resulting from human activities (subjective and objective expert opinions)	Semi-quantitative measure for management unit; mapping of spatially explicit risk values	No	(Irene et al., 2010)
Small (ca. 25.000km ²); South California, USA	Marine traffic	Multiple species (mammals)	Model output	Ship-strike risk = shipping routes [route-use overlay] in combination with whale distribution model [generalised additive model (GAM)]	Quantitative measures per unit area (4km ²); risk scores for different shipping scenarios	Yes, spatial scenarios for (alternative) ship traffic and military use, fishing and conservation (MPAs)	(Redfern et al., 2013)
Small (ca 10.000km²); Pudget Sound, USA	Multiple human stressors	Multiple species (fish)	Empirical data	Risk = direct impacts of pressures [mortality] and resilience [fecundity, behavioural/physiological response, life-history traits]; spatial overlaps between pressure and states of various ecosystem components	Semi-quantitative measure for given management units; risk maps and risk scores	No	(Samhouri and Levin, 2012)
Meso (500.000km ²); UK southern, eastern and western coastal	Aggregate extraction	Multiple species	Empirical data, expert knowledge	Risk = vulnerability [spatial overlap and statistical test]; sensitivity index [recovery potential (e.g. ability to switch diet and reproductive strategy)]	Quantitative measure per unit area (2*2nm); overlay map as vulnerability	Yes, current and future license areas have been considered	(Stelzenmüller et al., 2010a)

waters

Scale and location	Risk identification and char	acterisation	Risk analysis	5		Risk evaluation	References
Small (28.500km ²); German EEZ, North Sea	Fisheries	Single species (fish)	Empirical data	Risk = ratio of species abundance [environmental parameters (temperature, salinity and depth)] and catch in commercial fisheries using BN model	Quantitative measures per unit area (3*3 degrees); BN model output, vulnerability states	Yes, the impact of no-takes zones due to establishment of wind parks have been considered (changes in fishing effort distribution and temperature)	(Fock et al., 2011a)
Small (150.000km ²); Gulf of Finland	Nutrient loads	Habitat quality (water body)	Model output	Risk = phosphorus loads (t/year), nitrogen loads (t/year)	Quantitative measure for given management unit; mapping out approach of predicted concentrations	Yes, coupled model output using multiple scenarios	(Vanhatalo et al., 2013)
Large; Western and Central Pacific Ocean	Fisheries	Multiple species (sea birds)	Empirical data, expert knowledge	Risk = productivity (P) / susceptibility (S) [P = Fecundity Factors index; S = product of fishing effort and normalised species distributions weighted with vulnerability of species to longline fishing gear; vulnerability = number of kills reported]; PSA Analysis	Semi-quantitative measure per unit area (5*5 degrees); mapping out approach, summing up over all species, season and flag	No	(Waugh et al., 2012)
Large; Australian waters	Fisheries	Multiple habitats	Empirical data, expert knowledge	Impact = PSA (Productivity Susceptibility Analysis [productivity = level of natural disturbance, regeneration of fauna; susceptibility = availability, encounterability, selectivity])	Semi-quantitative measure for given management unit (30 or 60nm); risk category per habitat	No	(Williams et al., 2011)
Small (3800km ²); Rhode Island	Offshore wind farms	Multiple species	Empirical data, expert knowledge	Impact = concern index [sensitivity to displacement, weighting of species by species] to predict areas with high conservation priority in relation to their distribution (surface area)	Quantitative measure per unit area (2km ²); scenario output, mapping of vulnerability	Yes, Zonation software (Moilanen, 2013)	(Winiarski et al., 2014)

3.2 Case study

Fleet specific trawling frequencies show clear spatial patterns, and as an example we illustrated the spatial distribution of the mean trawling frequency of the international beam trawl fleet with 80 mm mesh size and > 221 KW overlaid with the current (2013) offshore wind development (OWD) application areas in Fig. 4. The mean overall local mortality rate assuming an equal impact of all fishing fleets is displayed in Figure 5 (top), where high values can be found in the North-East of the study area and along a coastal strip. The relative combined recovery rates of the benthic communities are fishery independent and therefore patterns resembled the benthic communities (Fig. 5; bottom). Spatial predictions of DI revealed that 5.3 % of the total area showed values > 1, indicating a higher rate of mortality than recover, whereas 0.74 was the maximum value estimated for the weighted disturbance indicator (DI_w).



Fig. 4. Mean (2005 - 2008) frequency of a unit area $(3 \times 3 \text{ nm})$ being reworked by the international beam trawl fleet with a mesh size of 80 mm and > 221 KW derived from VMS data (Beam80lrg) and additionally overlaid with the current (2013) offshore wind development (OWD) application areas.



Fig. 5. top: Relative overall local mortality rate (M) ($is_k = 1$) based on the distribution of the mean fishing frequency by the respective fleets; bottom: distribution of the estimated relative recovery rates derived from the combined recovery time and recover frequency of the prevailing benthic communities (see Table 1).

High values of the unweighted and weighted disturbance indicator were found in different places (Fig. 6). This is due to the fact that in the case of DI_w the beam trawl fleets using nets with > 800 mm mesh size (Beam80lrg and Beam80sml) were given by far the highest impact weights. For each BN node that represents a continuous variable the weighed mean (the mean value weighted by the probability of occurrence) with its Gaussian standard deviation is shown on the bottom of each node (Fig. 3). For instance the weighted mean state value for large beam trawl frequencies is 0.221 ± 0.34 indicating a high level of variance. The trained BN displays the "business as usual scenario" using the fishing effort patterns from 2005 - 2008, from which it was derived that 34.5 % of the total area showed the highest level of trawling frequencies (state 3: 0.06 and 1.16, Fig. 3).



Fig. 6. left: Estimated values of the disturbance indicator (DI) based on an overall local mortality rate with equal weight for the impact scores of the six fishing fleets; right: Estimated values of the disturbance indicator (DI_w) based on an overall local mortality rate with different weights for the impact scores of the six fishing fleets ($is_{\text{BEAM80}\text{lrg}} = 1$; $is_{\text{BEAM1631}\text{lrg}} = 0.1$; $is_{\text{OTTER80}\text{lrg}} = 0.15$; $is_{\text{OTTER80}\text{sml}} = 0.15$).

An alternative interpretation of the probabilities associated to the respective node states is that there is a 34.5 % chance to find a value between 0.06 and 1.16 within any given unit area (vector grid cell). The baseline BN showed further that there is a 4.12 % chance to find values of DI >1 within any given unit area. In contrast, there is only a 1.35 % chance to find values of DI_w >1 within any given unit area. The sensitivity analysis of the disturbance indicator node (DI) showed that the latter was most influenced by the findings for mortality (node M; variance reduction = 22.5 %), recovery (node R; variance reduction = 13.8%), combined recover frequency (variance reduction = 10.9%), and type of benthic community (variance reduction = 10.3 %), while all other nodes resulted in a variance reduction < 2 %. The classification success rate (spherical payoff) which ranges from 0 to 1, with 1 being the best model performance, indicated a relative accuracy of the BN model for predicting DI_w, respectively.

The effects of the planned offshore wind development sites on the two measures of benthic disturbance (DI and DI_w) were explored stepwise (Fig. 7a and b). Fig. 7a showed that the new prior distribution of the Beam80lrg node (corresponding to the spatial relocation of 15 % of the fishing activities) resulted in an average likely value of 0.31 for DI along with a standard error of 0.42. Compared to the "business as usual" scenario the predicted probabilities of the DI states only altered around 1 %. In contrast, using the same scenario the average likely value of DI_w increased from 0.235 (+/-0.27) to 0.261 (+/- 0.29). However, this increase was not significant due to the great variance in estimates. The additional modification of the prior distribution of the Beam1631sml node and the predicted probabilities of benthic disturbance states are displayed in Fig. 7b. The model predicted an average likely value of 0.309 for DI (+/-0.42), while the average likely value for DI_W remained the same. However, for this case study, where the BN is populated with spatial data, the likely values of the disturbance indicator averaged over the entire study area of minor importance (as indicated by the high standard error). Here, the predicted likelihood of an area proportion having a certain value is much more relevant to evaluate trade-offs of spatial management scenarios. Whereas the assumed redistribution scenario of both fleets showed no significant effect on the four DI states, overall changes were predicted in relation to the probability distributions of DI_w states. The estimated probabilities of DI_w values > 1 ranged between 1.35 % (business as usual scenario) and 1.63 % (full displacement scenario). This means that 1.63 % of the study area (or 1.63 % of all vector grid cells) will experience DI_w values > 1 using the current fishing effort displacement scenario. More relevant changes to the predicted probabilities were observed for the DI_w states 1 and 2. Compared to the baseline scenario the predicted probabilities of the DI_w state 1 decreased around 8 % (from 79.3 % to 71.9 %), while the probabilities of DIw state 2 increased about 6 % (from 16 % to 22.1 %). This means that 8 % of the area (8 % of the vector grid cells) will likely face a worsening of DI_w values compared to the current state. This is consequently related with an increased probability (by 6 %) for any given unit area to have a DI_w value ranging from 0.3 to 0.5.

Thus the here considered MSP measures and the related fishing effort displacement scenario would not fulfil the defined overall operational management objective ("*The average relative vulnerability of benthic communities to fishing should not deteriorate with respect to current levels*"), since the predicted probability distributions of the DI_w values showed deteriorating values compared to the current state.



Fig. 7a, b. Results of the inference the Bayesian belief network model applying the spatial management scenario "What are the likely impacts of spatial shifts of 15 % of the total fishing frequency of large beam trawlers (Beam80lrg) and 3% of the small beam trawlers (Beam1631sml) on local disturbance rates (assuming equal and weighted impacts of the different fishing fleets)". Predicted probabilities (%) are shown for all states of the relevant model nodes.



Fig. 7. continued

4. Discussion

4.1 Current ERA approaches and gaps in a spatial management context

We used the steps of a risk assessment framework described by (Cormier and al., 2013) to frame the assessment of a fair number of spatially explicit and quantitative ERAs concerned with spatial management questions. There are, of course, other established risk assessment frameworks such as a Productivity–Susceptibility Analysis (PSA) a semi-quantitative ERA methodology (Waugh et al., 2012) or the conceptual DPSIR (Driver-Pressure-State-Impact-Response) framework which illustrates cause-effect pathways (Elliott, 2002). Further bow tie diagrams describe and analyse risk events by visualising relevant pathways from causes to consequences (Ferdous et al., 2013). The bow tie diagram focuses on so-called barriers representing existing control or mitigation measures that are placed between the causes and the risk, and the risk and consequences. These diagrams can also be adapted to the DIPSR framework. Recently, BNs have been used in combination with bow tie diagrams to overcome their purely depictive capabilities by adding probabilities and conditional dependencies between components (Badreddine and Amor, 2013; Khakzad et al., 2013).

The here identified methodological shortcomings were based on a structured, but not exhaustive selection of studies. Nevertheless, this selection was a result of a literature database search (Scopus) using defined key-words, context and expected type of output. Review results showed that independently from the investigated ecosystem components, computing quantitative measures of sensitivity is still challenging and could hardly be derived from empirical data alone. Often a combination of model outputs and expert knowledge seemed to deliver the preferred metric e.g. (Foden et al., 2011). Thus our findings emphasised the lack of empirical studies to support extrapolation of measures of sensitivity to system scale questions (see discussion in (Crain et al., 2008). Another identified weakness was the lack of an explicit assessment of uncertainty, especially in cases where expert judgements were used. Uncertainty cannot be eliminated from any integrated assessment or model-based decision support, however it should be recognised and constructively handled (Astles et al., 2006; Rotmans and van Asselt, 2001). Thus the assessment of uncertainty is an important prerequisite of the herein described steps of risk analysis and subsequent risk evaluation. For instance fuzzy sets and advice theory allow for characterisation of uncertainty associated with expert knowledge (Ferdous et al., 2013). Also Walker-type and pedigree matrices were utilised to assess both the sources and respective relative levels of uncertainty related to an assessment process which integrates numerous sources of information and data qualities (Stelzenmüller et al., 2015b).

Despite the great variation of terminology across studies the minimum measure of vulnerability involved in all cases was a combination of a measure of sensitivity of an ecosystem component and the probability and magnitude of a stressor occurring. However, only a few studies computed vulnerability according to the best practices defined in (De Lange et al., 2010), which require the consideration of resistance and resilience when defining sensitivity and vulnerability, respectively. This depicts a future need to root spatially explicit quantitative ERAs more in ecological theory with regard to system function and processes (e.g. (Fock et al., 2011b).

Scenario evaluation is deemed as an important step in the risk assessment framework and which has been carried out in roughly half of the reviewed studies. Those who did simulate management scenarios generally used spatially explicit tools and approaches such as Ecospace (Fouzai et al., 2012), Zonation (Moilanen, 2013; Winiarski et al., 2014) or a combination of GIS and BN models (Fock et al., 2011a) to allow for a non-static assessment of cause-effect pathways.

Surprisingly, only one of the studies, included in this review, exploited a process-based numerical model to predict ecosystem responses to natural or human pressures (Vanhatalo et al., 2013). Process-based models represent physical processes and typically include forcing by waves and/or currents, a response in terms of sediment transport and a morphologyupdating module. Routinely used for reconstructions of past conditions or to forecast possible future trends, such models are useful in the context of risk assessments (Weisse et al., 2009), in particularly, when the simulations cover a wide range of natural variability. Building on hydrodynamic drift simulations, (Chrastansky and Callies, 2011a) have demonstrated how such model data can be turned into spatially explicit information on the risk posed by hypothetical oil spills in the North Sea. Their approach based on a BN, which makes the essential information of the model available without the need to access the memory-intensive, original data sets. In that way, detailed information on key natural drivers and their causal relationships with existing pressures can easily be considered in a wider GIS-coupled risk assessment framework. Until now, this is rarely the case in ERAs making it difficult (if not impossible) to separate the effects of natural disturbance, for example by waves, from that caused by human activities such as bottom trawling (Diesing et al., 2013). According to ecological theory (Pickett and White, 1985), disturbance regime is, however, an important

spatial process which should be accounted for when assessing the risks of spatial management scenarios.

4.2 Perspectives for assessing the trade-offs of MSP measures in the German EEZ of the North Sea

The aim of the case study was to address some of the methodological shortcomings identified in the current literature on spatially explicit and quantitative ERAs and to provide some perspectives for assessing the trade-offs of on MSP measures in the German EEZ of the North Sea.

We built on a study by (Fock, 2011a; Fock et al., 2011b) for calculating measures of fishing frequency, mortality rates and the disturbance indicators. The overall measures of recovery and mortality have been computed for ten benthic communities (Pesch et al., 2008). For this we converted existing model outputs on recovery and mortality rates by sediment type to respective rates by benthic community. This has been done by weighting sediment specific parameters with likely species habitat preferences given in (Rachor and Nehmer, 2003).

As a consequence, those benthic community specific estimates on mortality and recovery rates reflect rather rough estimates of those parameters. A promising alternative source for recovery rates (days) by phyla and habitat type provides a meta-analysis of trawl impact studies carried out by (Kaiser et al., 2006). In future studies, those results could be used to redefine for instance fleet specific impact scores (is_{fleet}) of the weighted mortality rates. Further, benthic disturbance was only calculated for infaunal benthic communities, while epifaunal species may be more vulnerable to fishing disturbance (Piet et al., 2000). Empirical data for instance revealed longer recovery times of benthic epifaunal communities (7 - 8 years) compared to infauna communities (2 - 5 years) in the German Bight (at least after the impact of cold winters) (Neumann and Kröncke, 2011). As a result, future steps to improve mortality and recovery rates of benthic communities would embrace the combination of infaunal and epifaunal recovery and decline rates.

In our case study we did not explicitly map or consider a measure of natural disturbance, however we can assume that natural disturbance, e.g. by tidal and wave stress as well as daily and seasonal temperature variability, is highest in shallow coastal areas (Becker et al., 1992; Neumann et al., 2013). Here, benthic communities will show greater resilience to fishing disturbance than in zones with larger water depths (e.g. (Hiddink et al., 2006c). Further (Elliott and Quintino, 2007) argued that communities in stressed environments are well adapted to natural stress and will probably never show a recovery to "undisturbed"

communities. Thus taking interactions between fishing and natural disturbances into account would very likely result in different patterns of the disturbance indicator. Nevertheless, (Fock et al., 2011b) suggested that observed recovery rates incorporate indirectly local effects of natural disturbance. Addressing a similar topic (Diesing et al., 2013) investigated the impact of demersal fishing on sea-floor integrity in the greater North Sea and proposed a method to incorporate natural and fishing disturbance in a spatially explicit study. They defined trawling impact as significant when it exceeds natural disturbance (by waves and tides). The resulting indicator was expressed as a probability on a 12x12nm grid and could as such be rescaled and incorporated into our risk assessment approach.

The observed differences in spatial pattern of the two disturbance indicators were clearly a result of the weighting of the impact of the different fishing fleets. Hence DI and DI_w describe a range of likely outcomes of disturbance modelling with DI_w as lower and DI as upper bound. In this sense it reflects a transparent assessment of uncertainty.

To enable a dynamic link of risk analysis and risk evaluation, hence scenario evaluation, we combined GIS with a BN model to conduct a quantitative spatially explicit risk assessment. For the integration of BNs and GIS we followed in general the good practice described in (Johnson et al., 2012). BNs indeed are advantageous, especially when considering the input from various data types (Aguilera et al., 2011), but model construction often is challenging and nontrivial (Kjræulff and Madsen, 2012). BNs represent multi-dimensional distributions and can conveniently be applied for updating probability distributions of all variables given observations for just a subset of them. Information available will propagate across the whole network regardless of the orientation of edges (see e.g. (Kjræulff and Madsen, 2012). This analysis of joint probabilities based on incomplete observations must be distinguished, however, from predicting the results of external interventions (e.g. scenario assessment). For the latter purpose a BN must be formulated in line with causal relationships (see (Pearl, 2000). According to (Kjræulff and Madsen, 2012) a BN is a probabilistic network for reasoning under uncertainty, whereas an influence diagram is a probabilistic network for reasoning about decision making under uncertainty. Thus an influence diagram represents parameters actively controlled by rational decision-makers as non-random decision nodes. They rate system configurations that result from management decisions based on value or utility nodes (Pearl, 1988; Bedford and Cooke, 2001). In our example we did not construct an influence diagram with decision nodes. Further multistage decision networks allow even for considering a sequence of decisions at future points in time when certain types of information will become available. Such repeated decision making is an essential part of an adaptive management process (Vugteveen et al., 2014). A representation of such practically relevant concepts in a probabilistic framework such as the one illustrated here, however, is scientifically challenging and requires future development.

Our spatial management scenario simulated a general spatial shift of fishing effort from medium fished areas to low and highly fished areas due to the development of offshore renewables in areas where 15% and 3% of the total average beam trawl effort took place. This was based on the assumption that vessels conducting demersal mixed or crustacean fishery reallocate their effort in areas of potential large catch or previous knowledge and experience (Bastardie et al., 2013a). Results showed that the assumed shift in fishing frequencies did not result in significant changes of the average likely value of the disturbance indicator. However, disturbance indicators (assuming unequal impact) still worsen in approximately 8% of the study area. This information is much more meaningful when evaluating the trade-offs of spatial management options. Once, more realistic fishing effort displacement scenarios become available, the combined GIS and BN approach can be used to predict likely local values of e.g. the disturbance indicator. For instance individual based models, predicting fishing fleet behaviour under changing economic or ecological conditions (Bastardie et al., 2013b), would allow entering specific findings for prior distributions of fishing frequencies of specific fleets.

5. Conclusion

Currently, quantitative ERA studies in a spatial management context reflect a wide range of assessment approaches, with varying interpretations of the terms risk, vulnerability or impact. Especially the different definitions of vulnerability suggest that future spatially explicit quantitative ERAs should be more rooted in ecological theory with regard to system function and processes. Spatially explicit risk assessments yet to come should also consider the inclusion of numerical models for instance describing natural disturbance, since this is an important component in ecological disturbance theory. We identified a transparent assessment of uncertainty as clear shortcoming of many current approaches and conclude that the application of Bayesian belief networks are a promising approach to address this. Also future research is needed on how to build meaningful influence diagrams, with parameters actively controlled by rational decision-makers (decision nodes), in the course of quantitative ERAs. Independently from the concepts and methods applied to predict a measure of risk, we strongly recommend putting caution on the type of output produced and its potential uptake in an actual spatial management process. The latter often refers to complex multiple

objectives settings, where the impacts of numerous human activities need to be jointly assessed. In conclusion, marine spatial management or MSP processes should embed ERA frameworks which allow for the integration of multiple risk assessments and the quantification of related uncertainties at a common spatial scale.

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Chapter 5

Exploring the effects of spatial planning and climate change on marine fish biodiversity with the help of spatially explicit Bayesian Belief Networks

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Abstract

Maritime Spatial Planning (MSP) is mandated to coordinate different human activities in space to achieve sustainable use of resources without compromising marine biodiversity and ecosystem health as demanded by the Marine Strategy Framework Directive (MSFD). To implement this challenging task holistic spatial management assessments are essential to identify and weigh risks and uncertainties of spatial planning decisions on marine biodiversity. This should include compliance to management, which is often neglected in assessments, as well as natural variability and climate change. The effects of area closures due to offshore wind farms (OWF) along with the implementation of the Natura 2000 network will lead to a displacement of fishing effort. Cause-effect pathways are often not known and thus it is unclear in how far marine biodiversity will be affected at scales relevant for MSP. We propose Bayesian Belief Networks coupled with a Geographical Information System to spatially predict changes on demersal fish biodiversity due to different levels of area closures, compliance rates, protection effects and temperature increase. We simulated various short (5 year) and mid-term (15 year) scenarios in the German EEZ of the North Sea using a suite of taxonomic indices at the species and community level as well as a novel trait-based indicator. We defined cause-effect pathways between fishing and biodiversity indicators and used empirical data and qualitative information to simulate effects on demersal fish. Our findings suggest that conservation effects through area closures outweigh negative effects from relocation of fishing effort but that non-compliance can locally hamper recovery. Increase in fishing effort did not lead to any significant decline in biodiversity indices at the EEZ scale and effects of area closures were most prominent around closure. EEZ wide effects were only caused through a simulated temperature increase. Conservation success will thus also depend on factors that are not controllable by management with differing risks and opportunities for the recovery of species and communities. While almost all scenario combinations predicted increased probabilities of recovery, the trait-based indicator faces the greatest risk and will likely decline when temperature increases. In conclusion, MSP processes should incorporate spatial management assessments which allow for the integration and the quantification of related risks as well as uncertainties at a common spatial scale.

Keyword: Bayesian Belief Networks, Marine Spatial Planning, management scenarios, Natura 2000, offshore wind farms, fishing displacement

1. Introduction

The Southern North Sea is one of the most intensively used marine areas in the world where various types of human activities are competing for space (Emeis et al., 2015). The policy landscape governing these different user interests is likewise highly complex, overlapping and not integrated in practice (Qiu and Jones, 2013b; Boyes et al., 2016; Jones et al., 2016; Janßen et al., 2017). The Maritime Spatial Planning Directive (EC, 2014) and subsequent national maritime spatial plans (MSP) that have ordinance to regulate spatial management processes are usually not cross-sectoral (Jones et al., 2016). Further, the implementation of ecosystem-based management (EBM) poses difficulties to national agencies (Jay et al., 2016). Major spatial conflicts exist between the massive development of offshore wind farms (OWF), conservation needs and the fishing sector. Large areas will be closed for certain fishing métiers to conserve sensitive habitats as part of the Natura 2000 networks under the Habitats Directive (EC, 1992). In most countries fishing is further excluded from OWFs. Though not a management tool per se, they function *de facto* as marine protected areas. One of the future challenges in European seas will therefore be achieving a balance between the sustainable use of marine resources with conservation of biodiversity, ecosystem health and functioning, as e.g. demanded by the EU Marine Strategy Framework Directive (MSFD) (EC, 2008).

Several studies on ecosystem effects of OWFs on the demersal fish fauna describe positive effects caused by the exclusion of fisheries and increased food availability and shelter provided by turbines (Ashley et al., 2014; Gasparatos et al., 2017; Langhamer, 2012; Hammar et al., 2016). The increase in species-specific abundance, length and biomass was however only analysed at the scale of the farm and there is still a lack of information at ecological relevant scales (Lindeboom et al., 2015) as well as on effects on overall fish biodiversity (Inger et al., 2009). Plenty of literature exists on benefits of marine protected areas (MPA), which mostly describe increases in target species abundance, biomass, individual size, and egg production after partial or complete exclusion of fishing (see Goñi et al. (2011), Gell and Roberts (2003) and references therein). Increases of biodiversity and spillover (emigration from the reserve into fished areas) were seldom documented for partially protected or temperate areas. Fisheries regulations under Natura 2000 will provide partial fleet-specific protection with fewer constrains for static gear types (BMUB, 2016). One of the already existing reserves in the North Sea, the Plaice Box, has been closed to large beam trawlers since 1995 to protect major nursery areas of

plaice (*Pleuronectes platessa*) and reduce its discarding. Studies showed that juvenile plaice moved to deeper waters outside the Plaice Box, which is explained by eutrophication and temperature changes (Beare et al., 2013; van Keeken et al., 2007). Projected sea surface and bottom temperature increases will therefore influence the performance of area closures and alter communities by favouring more tolerant or warm-water species (Quante and Colijn 2016). The performance of closures will also depend on whether fishermen will comply with regulations. A lack of compliance was e.g. one of the likely factors that explained why after a six-year closure off the US Atlantic coast no positive effects were measured for fish abundance (Bacheler et al., 2016). Finally, fisheries closures, either by reserves or OWFs, were controversially discussed. Benefits due to conservation could be foiled by fisheries displacement which can reduce the overall sustainability (Greenstreet et al., 2009; Hilborn et al., 2004). Modelling approaches to predict socio-economic effects of spatial shifts in fishing effort and/or effects on target species after area closure were already developed (Bastardie et al., 2010; Lehuta et al., 2010). However, effort displacement remains hard to predict not the least due to inter-annual changes in target species distributions. Further, it depends on a variety of different socio-economic, social and ecological factors introducing additional uncertainty towards quantifying environmental effects of displacements (Slijkerman and Tamis, 2015).

Stimulated by the MSFD requirement to establish a monitoring programme and the availability of fine-scale information on the distribution of fishing activities from vessel monitoring system (VMS) data, research currently focusses on indicator development (Probst et al., 2013), mapping distributions of key ecosystem components (Rambo et al., in press), the frequency and intensity of human uses especially fishing (Campbell et al., 2014) as well as research to assess effects of trawling on benthic ecosystems (Rijnsdorp et al., 2016; Hiddink et al., 2016). However, sectoral assessments such as environmental impact assessments of planned OWF developments required by law (Vaissière et al., 2014) will not suffice. Decision making will become more complex in the future and the risks, opportunities and consequences of spatial management options on the ecosystem need to be evaluated in a holistic way that includes compliance to management measures often neglected in assessments as well as natural processes such as climate change.

As yet, such holistic assessments are lacking. Complex end-to-end ecosystem models, such as ATLANTIS (Fulton et al., 2011) or EwE and Ecospace (Christensen et al., 2009), exist that can be used in a management strategy evaluation. These tools are however very data and parameter

intensive and model complexity leads to an increase in parameter uncertainty (Collie et al., 2014). Further, bio-economic models are available that specifically model effects of fishing displacement due to (spatial) management measures such as DISPLACE (Bastardie et al., 2014) and FISHRENT (Simons et al., 2014). These models focus on target species' stocks rather than assessing biodiversity or community level effects. Additionally, uncertainty is rarely made explicit.

For the evaluation of risks and consequences of management measures, Bayesian (belief) networks (BN) provide a valid addition to the modelling toolbox (Ascough II et al., 2008). BNs have been used in a range of different risk assessment and management contexts and are becoming quite popular in environmental modelling (McCann et al., 2006; Uusitalo, 2007; Franco et al., 2016). BNs are probabilistic models that display correlative and causal relationships by first setting up a conceptual model (a directed acyclic graph, DAG) representing the best available knowledge about system functioning. The probabilistic relationships between model components (nodes) are then specified by conditional probability tables (CPT). These relationships or cause-effect pathways can either be inferred or learned from the correlation inherent in the data, or they can be specified by expert knowledge or equations derived from external models. BNs are capable to combine qualitative and quantitative data and make uncertainty and risks explicit by providing probability distributions for each model component. In addition, different spatial and temporal scales can be represented in one model (Wooldridge et al., 2005). Although not designed as a spatial modelling tool, they have been used in spatial assessments by modelling spatial dynamics separately and including results into BN nodes (Grêt-Regamey et al., 2013a), implicitly by representing each sub-set of the study area by a node (Chrastansky and Callies, 2011b), or by fully integrating with a geographic information system (GIS) (Stelzenmüller et al., 2010b; Verweij et al., 2014; Liu et al., 2016). GIS-BN frameworks have already been used in a similar context to test effects of fisheries displacement on benthic communities (Stelzenmüller et al., 2015a) and plaice (Stelzenmüller et al., 2011).

Here, we use a spatial BN to assess the risks, opportunities and consequences of future spatial management measures, i.e. the exclusion and subsequent reallocation of the international bottom trawl fleet from OWFs and Natura 2000 sites, on the sensitivity and biodiversity of demersal fish in the German EEZ of the North Sea. The conservation of biodiversity is a cross-cutting theme in most marine policies and a thematic link between the MSFD and MSP (Rambo et al., in press).

Currently, 2.6 % of the German EEZ of the North Sea is closed to fishing due to OWFs, and further constructions are planned and partly already approved. While in Germany, OWF development plans have effectively been reduced from contributing 25 GW to 15 GW to the German energy budget until 2030, in combination with the proposed Nature 2000 sites, this would still amount to an area loss for bottom trawl fisheries of about 28 %. We structured our analysis using elements of the risk-based approach outlined in Stelzenmüller et al. (2015) and based on a scheme developed by Cormier (2013). We first identified activities causing risks to the environment, along with relevant management measures and key ecosystem components. Risk analysis requires a measure of sensitivity or vulnerability of the ecosystem component to the respective pressure. In our model sensitivity was intrinsically embedded in the indicator and was derived by the BN through the correlation found in the data. Finally, we evaluated risks by means of a suite of management scenarios. We developed 10 scenarios over two time horizons, namely 2020 and 2030, representing the two cycles for OWF development approvals. In our scenarios we tested the effects of proposed management measures (area closures) on a suite of biodiversity indicators to assess effects of management options. We further investigated management compliance, a simulated temperature increase including the contribution of important environmental drivers, as well as direct reserve effects inside and in the vicinity of the closed areas (considering species immigration into the closed area and spillover). We considered single as well as combined effects of these factors. Finally, we tested whether good environmental status (GES) to be achieved under the MSFD until 2020 would be likely under these scenario conditions.

The aim of this study is first to develop a conceptual model (DAG) depicting the key agents and ecosystem components. Secondly, we examine cause-effect pathways between fishing effort, environmental drivers and biodiversity indicators by combining empirical data as well as literature-based expert judgment to define the CPTs. Finally, we explore risks of future spatial management measures on biodiversity state in the German EEZ of the North Sea by means of BN scenarios and derive lessons learnt for the German MSP and MSFD process.

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2. Material and methods

2.1 Case study area and spatial management measures

Our study area comprised the German EEZ of the North Sea and adjacent coastal waters (see Fig 1). The key components in relation to the research question and study area are: bottom trawling pressure of the three international bottom trawl fleets, a suite of biodiversity related state indicators, namely species richness, the community sensitivity index to fishing (CSI), and the CPUE of cod, all existing and future spatial management measures, depth, sediment and sea bottom temperature (SBT). All components are further explained below and in Table S1 (supplementary information).



Fig. 1. Important spatial components of the BN: a) Depth profile, b) mean December sea bottom temperature, c) sediment distribution, d) Natura 2000 sites, e) different stages of OWF developments as well as numbered clusters for OWF developments (cluster 9 - 13 for potential future OWF developments after 2030), and f) the Plaice Box.

We used the Natura 2000 sites in which fleet-specific fishing restrictions are proposed. In the German EEZ of the North Sea these areas comprise the Borkum Reef Ground, Dogger Bank and Sylt Outer Reef including the Amrum Bank (Fig. 1d, (BMUB, 2016)). The Amrum Bank will be

closed for all fishing activities, while in all remaining areas static gear may still be allowed. Further, the eastern part of the Sylt Outer Reef, with exception of the Amrum Bank, will not be closed for the traditional shrimp fishery (small beam trawls), but for otter trawls and large beam trawlers targeting flatfish. The management plan to implement the German Nature 2000 sites is not finalized yet. For the purpose of this paper we assume that area closures will be already effective from 2017 onwards.

We obtained shapefiles of existing and planned OWF sites from the BSH and generated a 500 m buffer around each area. In Germany OWFs including a 500 m safety zone are permanently closed to any fishing activity. A recent renewable energy law (EEG 2017) regulates that providers have to compete for building permission, also affecting already existing permissions (BSH, personal comment). The next phase of park constructions, to be completed until 2020, are developments which have a binding promise to receive grid connection from the Bundesnetzagentur (Federal Network Agency for Electricity, Gas, Telecommunications, Post and Railway): (http://www.bsh.de/de/Das_BSH/Bekanntmachungen/Bekanntmachungen_ Windparks/Liste_WindSeeG.pdf). All further providers have to compete for remaining areas in cluster 1 to 8 of the Bundesfachplan Offshore (http://www.bsh.de/de/Meeresnutzung/BFO/ Dokumente/BFON_final.pdf) (Fig. 1e). Therefore, it is still uncertain whether all planned OWFs will be built in order to reach the predefined target of 15 GW until 2030. We therefore grouped all OWFs into three groups specifying whether the areas were already closed to fishing in 2015, whether they are to be built until 2020 or until 2030.

2.2 DAG and BN development

To develop the BN, all spatial data were projected to a common spatial grid of 5 x 5 km², which corresponds to the resolution of the biological indicators and data were subsequently used to develop the DAG and respective BN (Stassopoulou et al., 1998). We used a nested approach to building the BN models, all of which were conducted using the BN modelling shell Netica (www.norsys.com). First, we set up a core model (Fig 2a) representing the main cause-effect pathways between fishing pressure, natural variability and biodiversity state. The distribution of species and assemblages are driven by biotic processes and environmental drivers and are shaped by anthropogenic activities, mainly fisheries (Foden et al., 2011). CPTs of each node were filled with empirical data from our study grid (Chapter 2.2 Table S1). We then trained CPTs of the

biological indicators with the probability distributions of fishing effort and key environmental variables to quantify pressure-state relationships between these variables (Marcot et al., 2006b). The fishing effort in the core model is already affected by existing spatial management measures such as OWFs and the Plaice Box (Fig. 1). We therefore did not use these nodes to train the net.



Fig. 2. Conceptual models of a) the main cause-effect pathways (core model), b) fishing effort redistribution sub model, and c) the full model.

Secondly, we built a top-down fishing effort redistribution sub model (Fig. 2b). In a management context, regulations are implemented to reduce the negative environmental impact of an activity. Here we consider measures that spatially exclude specific fishing métiers. Therefore, fishing effort is effectively reduced to zero in closed areas, whereas it is locally increasing due to redistribution in the remaining areas. The success of a management measure in order to reduce a pressure also depends on the level of compliance of agents (Bloomfield et al., 2012). For the redistribution sub model we included all existing and planned fisheries restricted areas as well as empirical and estimated compliance rates. From this we derived a spatial compliance node by manually filling in the CPTs; e.g. setting 100% probability to "outside" if the parent node indicated being outside of the closed area and setting a 100% to compliant or non-compliant if the combination of parent nodes was "inside" and "compliant" or "non-compliant", respectively. The redistributed effort is displayed by the Residual effort nodes, a child node of the original fishing effort from 2015 and the spatial compliance node. According to Murawski et al. (2005) and Hiddink et al. (2006a) we assume that fishermen affected by area closures move to other
known fishing grounds and/or keep fishing in the vicinity of the closure. When using a BN for spatial predictions the model is applied to every grid cell of the prediction grid so the information, in our case whether a grid cell is within a known fishing ground or within a certain distance to a closed area, needs to be included in the BN model as well as in the prediction grid. We therefore introduced two more parent nodes, the Principle fishing area nodes for each fleet and the Buffer zone nodes for each area closure. The CPTs of the Residual effort nodes were then filled based on expert judgement derived from literature and empirical data further explained in section 2.2.7.

Finally, we constructed the full scenario models by connecting the core model with the redistribution sub model (Fig. 2c). We replaced the link between the biological indicator nodes and the initial fishing nodes with the residual effort nodes from the sub model while maintaining the previously trained CPTs of the indicator nodes. Fishing restriction zones can also have a more direct impact on ecosystem components other than the exclusion and reallocation of effort. They can provide shelter and improved food availability (reef effect) such as in the case of OWFs whose structures can act as attraction devices (Langhamer, 2012; Rostin et al., 2013; Wilson and Elliott, 2009). Protected areas can lead to increased production and subsequent emigration (spillover) into surrounding areas (Goñi et al., 2011; Stobart et al., 2009). These additional protection effects are accounted for by the protection nodes in the full models. The CPTs of the protection nodes were filled by specifying if...else statements (section 2.1.8).

To summarise, all nodes but the residual effort nodes, buffer nodes, spatial compliance nodes and protection nodes are based on empirical data. The cause-effect pathway between fishing, environmental variables and biological indicators was inferred from the data described in section 2.1.4 and used to update the CPTs of all biological indicators. The CPTs of spatial compliance and residual effort have been filled by decision rules, the latter based on expert judgement. The CPTs of the protection nodes were specified via equations based on expert judgement (peerreviewed information). We therefore made full use of all three possibilities in a BN to define CPTs. Finally, we used the full model to spatially predict the distribution of biodiversity indicators under various realistic short- and mid-term management scenarios. Below the nodes, cause-effect relationships and scenarios are explained in more detail.

2.2.1 Fishing pressure

We produced maps of annual fishing effort for the main international bottom trawl fleets based on Vessel Monitoring System (VMS) data. VMS data provide information on vessel position, speed and heading at least every 2 hours. When they are combined with logbook data they provide detailed information on catch, landings and the gear used. Because logbook data were not available for non-German vessels, we distinguished fishing segments on métier level 4, i.e. the primary gear type (Rambo et al., in prep.). Further, small and large beam trawlers were separated by engine power (>< 221 kW), which is in accordance to the regulation of the Plaice Box (EC, 1998). This allows largely distinguishing the near-coastal shrimp fishery with small beam trawls from the offshore flatfish fishery, mainly targeting sole and plaice, which use larger beam trawls with different ground gear. We considered these fleets separately because Natura 2000 regulations as well as the disturbance of the ecosystem are gear-specific (Depestele et al., 2014).

First, data from 2008 until 2015 were cleaned according to the methodology described by Hintzen et al. (2012) using the VMStools package (Hintzen et al., 2014) and the software R 3.0.3 (R Core Team, 2013). Then, vessel state was identified based on speed frequency histograms and only pings identified as "fishing" were used for further analysis. To calculate trawl paths from VMS pings, we interpolated 98 points between two succeeding fishing pings with the cubic Hermit spline method (Hintzen et al., 2010). The distance between spatial fishing points was then multiplied with the corresponding gear width. Finally, these values were aggregated on a 5 x 5 km grid for each year and divided by 25 (the size of a single grid cell) to get a gear-specific annual swept area ratio (SAR) per grid cell (Fig. S1, supplementary information). A SAR value of 1 corresponds to a grid cell being completely trawled once per year. For the BN models we used fishing effort estimates from 2015 only (Fig. 3), whereas previous years were used for analysing fleet behaviour and compliance rates following area closures (section 2.1.5 & 2.1.6).



Fig. 3. Mean annual distribution of fishing effort [swept area ratio; SAR] in 2015 for the three main international bottom trawl fleets (small beam trawls, otter trawls, large beam trawls; from left to right) interpolated from VMS data. Relevant areas already closed to fishing in 2015 (Plaice Box and OWFs) are superimposed.

We also defined principle fishing areas (PFA) for each fleet and constructed a 10 km buffer zone around closed areas in GIS as further input for the redistribution sub-model. To derive PFAs we followed the approach of Fock et al. (2008) where for each year, the area in which 75% of the total effort was concentrated was determined (Fig. 4). The PFA is then defined as the maximum extent of the composite areas with a minimum size of 3 adjacent grid cells. We calculated the PFAs based on data from 2012 to 2015 only, to be consistent with the changed regulation in 2012, under which vessels from 12 to 15m total length need to be equipped with VMS as well.



Fig. 4. Principle fishing areas (PFA) for each fleet with superimposed OWF and Natura 2000 sites.

2.2.2 State indicators

The many interpretations of biodiversity resulted in a large variety of different indices, capturing different aspects of biodiversity (Di Battista et al., 2016). Most studies of biodiversity therefore apply a suite of indicators (Farriols et al., 2017). We chose two community-level and two species level indicators. First of all, species richness (S), defined as the number of species, remains largely synonymous with biodiversity in a policy context. We further used a novel functional trait-based indicator, the community sensitivity index to fishing (CSI, Rambo et al., in press), which was developed to identify fish communities with a species composition that would render them particularly sensitive to increases in fishing pressure. The CSI is computed as a sum of species specific sensitivity indices (SIs) published in Greenstreet et al. (2012), weighted by the individual species' CPUE, and standardised by the total number of individuals caught: $CSI = \frac{\sum_{i=1}^{n} n_i SI_i}{N}$, where n_i is the number of individuals of species i, N is the total number of individuals and SI_i is the SI of species i. The CSI ranges from 0 to 1 and indicates that a community is largely dominated by resilient (fast growing, early reproducing, small bodied) individuals when the overall value is below 0.165, whereas a value above 0.31 would be indicative of a community dominated by sensitive (large bodied, slow growing and late reproducing) individuals. Distribution of single species is also an MSFD indicator under descriptor 1 (biodiversity). However, there is so far no final agreement upon which species to monitor. For the BN approach, we chose cod (Gadus morhua) because it was identified as being sensitive (SI = 0.333). In addition, threatened species which are listed under the national Red List are of particular interest in an MSP process (BSH, pers. comment) and cod is classified as prethreatened in German waters of the North Sea (Thiel et al., 2013).

We used distribution maps from Rambo et al. (in press) of all four indicators. Individual species distribution maps were derived by aggregating data from samples collected in December 2005, 2009 and 2013 with a 7 m beam trawl equipped with a 20 mm cod end-liner and standardised to a trawling duration of 15 minutes during the German Autumn Survey in the Exclusive Economic Zone (GASEEZ). Point data were then interpolated using ordinary kriging. The CSI and S maps were then derived by a so-called indirect mapping approach by stacking all individual species distributions and calculating each indicator per grid cell.

2.2.3 Environmental factors

Sediment, depth and temperature are important predictor variables for cod and have been used to model the distribution of North Sea cod (Stelzenmüller et al., 2005; Hedger et al., 2004) as well as biodiversity (Callaway et al., 2002). Cod is a cold water species and specifically juvenile cod prefer a more structured habitat to seek shelter from predators (www.fishbase.org). Rambo et al (in prep) described that the CSI was strongly positively correlated with depth and showed a unimodal relationship with temperature. Increases in S of the fish community in the North Sea over the past 30 years was attributed to increasing temperatures (Hiddink and ter Hofstede, 2008). Depth and sediment data were provided by the German Maritime and Hydrographic Agency (BSH, www.bsh.de). Sea bottom temperature (SBT) data for December 2015 was derived from (Núñez-Riboni and Akimova, 2015).

2.2.4 Pressure-state relationships

In a management assessment context, describing or quantifying pressure-state relationships between fishing pressure and biodiversity state is the biggest challenge and likewise crucial for the model setup. Pressure-state relationships between fishing and community-level biodiversity is difficult to quantify specifically for S (Rochet and Trenkel, 2003). Rambo et al. (in prep) showed that the CSI significantly decreased with increases in fishing effort in areas which are mainly fished by shrimp trawlers (i.e. small beam trawls in coastal areas and the Inner German Bight). However, the relationship was less pronounced or even reversed in some offshore areas where otter board trawls concentrate. First, we analysed the relationships between indicators, environmental variables and fishing pressure from the three bottom trawl fleets by means of simple scatterplots (see Fig. S2 and S3, supplementary information, for relationships between variables from empirical data and from the inferred, trained core model). We then chose to link each indicator with the fleet that showed the strongest influence (a decrease in value with an increase in fishing effort). This also helped us to define BN node states. The biodiversity indicators CSI and S were only related to one fleet in the model that showed the strongest relationship in the previous analyses (Fig. S3, supplementary information). While indicators will also be affected by effort exerted from other fleets, the distribution maps of all indicators used to determine the pressure-state relationship in the core model are a result of the entire fishing effort in the study area and thus not independent from other fleets. For BNs it is further suggested to limit the number of parent nodes to three to avoid spurious inference (Marcot et al., 2006b).

2.2.5 Compliance with management measures

Compliance is key to an effective management. To estimate compliance rates for existing area closures (the Plaice Box and OWFs) we analysed fishing polls between 2008 and 2015. During this time a total of 119 large beam trawlers fished in German waters of the North Sea and 55 vessels did fish at least once inside the Plaice Box. Fishing polls were however mostly occurring close to the border and the Frisian Islands, the latter being outside our study grid. VMS polls identified as fishing from inside the Plaice Box effectively reduced from 1305 registered polls in 2008 to 366 in 2015 likely due to the ongoing north-western shift of plaice out of the Plaice Box into deeper waters (van Keeken et al., 2007). Because of this declining trend, we only used fisheries data from 2015 and identified all grid cells completely situated in the Plaice Box where fishing pings from large beam trawlers were registered. We then calculated the proportion of Plaice Box grid cells with fishing pings from the total amount of grid cells in the Plaice Box: 1 - N Plaice Box grid cells_(fishing pings) / N Plaice Box grid cells_(Total); which resulted in a compliance rate of 0.84.

We derived an annual compliance rate empirically from all OWFs in the German EEZ that were closed to fishing in 2014. This rate is based on the total number of fishing pings and active vessels in the OWF areas between 2008 and 2015 and the number of pings or vessels still registered in OWF areas after it was closed to fishing: 1 - N (vessel/fishing pings after area closure)/ N (Total vessels/pings). We excluded registrations from two vessels that are commonly chartered for monitoring purposes. Closing dates for OWF development sites were provided by BSH (Table S.2, supplementary information).

Fig. 5 shows that with the exception of two OWFs, compliance was very good or even 1 (perfect compliance). For the two OWFs compliance improved in the third year of closure, around the time when both parks became fully operational. OWFs need to be fitted with Automatic Identification System (AIS) receivers that record every vessel that passes through the closed area, which is one possible explanation for the overall very good compliance. The comparison between compliance rates derived from vessel or VMS recordings, respectively, shows that while several vessels fished inside OWFs the overall fishing pressure was rather low.



Fig. 5. Annual compliance rate of trawlers in OWFs after each year since the respective closure to fishing calculated from a) VMS recordings and b) the number of vessels.

In the model we therefore assumed perfect compliance to area closures around OWFs three years after they became effective and calculated a mean compliance rate for the first three years based on the recordings from all ten existing OWFs, which resulted in a compliance rate of 0.96. We then attributed the remaining 4.35% non-compliance randomly to the grid which corresponded to 2 - 3 grid cells for the different scenarios, respectively.

Given that Natura 2000 management plans have not been implemented yet, a comprehensive enforcement strategy is not known, which makes it difficult to foresee how compliance will turn out in the future. It is however likely that compliance rates will be similar to estimated Plaice Box rates, because Natura 2000 sites will also be partially protected zones and will likely not be equipped with an AIS. Here, we assumed that in approx. 20 % of the protected zones fishing would continue. We assigned these 20 % to grid cells in which fishing previously took place because it's unlikely that non-compliance would concentrate in previously unfished areas.

2.2.6 Redistribution of fishing pressure

Predicting fishermen behaviour after an area closure is highly uncertain, especially due to variability in distribution of target species. Redistribution has been modelled by several authors (Bastardie et al., 2010; Hutton et al., 2004; Bastardie et al., 2013a) and empirical evidence that fishermen accumulate at borders of closures (fishing the line) has been presented for marine reserves (Murawski et al., 2005) and OWFs (Vandendriessche et al., 2013). When an area is closed to fishing, fishermen have different options: They can keep fishing in the vicinity of the

closure, relocate to other priority fishing areas, explore new fishing grounds, change their fishing gear and thus the target species, resign their business, or simply continue fishing in closed areas (compliance < 100%). Which of these options is the most likely depends on a range of different economic, social and ecological factors. Generally, fishermen need to reduce additional costs caused by area closures. Based on a literature review, Slijkerman and Tamis (2015) identified a multitude of influencing factors. These are: The importance of the closed fishing ground (size and place), space limitation and competition with other vessels, spillover of fish and distance to borders of closed areas, the expertise and character of the skipper, fishing rights and quota for target and bycatch species, area specialisation and tradition influencing the ability to adapt, distance to the landing port (costs, including fuel price), preferred habitat of target species and temporality of area closure.

Many of these factors require detailed knowledge at the vessel level including fishermen's declaration of catches in logbooks and sales slips from fish auctions. International logbook data were not available and making assumptions from national VMS and logbook data to extrapolate to the international fleet (Hiddink et al., 2006a) was not feasible, as the German fleet only makes up to 20% of the entire fishing effort in German North Sea waters. We therefore analysed changes in fishing effort distribution between 2010 and 2015 as proxy for catch data and determined the level of displacement that took place over this period to derive decision rules at the fleet level. Displacement can be quantified simply by dividing the current amount of fishing effort inside the future closed areas from the total fishing effort (here within the study area) (Chollett et al., 2016). In 2015, 2.6 % of the area was closed to fishing due to OWFs. Based on SAR estimates from 2010, 3.6 % of total small beam trawl effort, 4.8 % of large beam trawl effort, and 1.8 % of otter board trawl effort was displaced from these OWFs. Overall, relative fishing effort between 2010 and 2015 has decreased in future OWF development sites but not in Natura 2000 sites (Fig 6). Small beam trawls will clearly be least affected by these planned area closures whereas otter board trawls will have to relocate the most from Natura 2000 sites and large beam trawls from planned OWFs until 2030.



Fig. 6. a) Total fishing effort [SAR] between 2010 and 2015 in the study area, and b) to d) percentage of fishing effort in future closed areas (Natura 2000 and OWFs) in relation to the total effort estimated in each year (potential displacement).

In general, total annual effort (Fig. 6a) and changes in fishing patterns during 2010 and 2015 (Fig 3) showed inter-annual variability and overall changes that could not be directly attributed to fishing exclusion from OWFs. Changes in target species distribution, e.g. of brown shrimp (Schulte et al., 2015) and plaice (van Keeken et al., 2007), are more likely reasons. The shift of plaice led to an increase in large beam trawl effort in the Dogger Bank in recent years, which will be partially closed to trawling when Natura 2000 areas are implemented. We did however find increases of effort around OWFs in the Eastern German Bight as well as decreases in the Inner Western German Bight. We then analysed fishing polls from individual vessels most affected by OWFs and found that behaviour depended on the size and location of the closure. If the area was part of a main fishing ground, 50 % effort remained in the vicinity of the closure and 50 % relocated to PFAs or to fishing grounds outside the study area. However, overall fishing effort at the fleet level did not significantly decrease between 2010 and 2015. Finally, if the area was never fished its vicinity was not visited (no fishing the line, no attraction due to potential spillover).

We applied the following decision rules to populate the CPTs of all three residual effort nodes which we generally applied to all three fleets equally. When one or more of the parent nodes indicated compliance we set 100 % to state 1 (no effort). If one or more parent nodes indicated non-compliance we set 100 % to state 2 (low effort), unless initial effort was medium or high. In the latter case we attributed up to 30 % to state 3 (medium effort) for combinations where the PFA was "inside". In cases where state combinations would be mutually exclusive in a grid cell such as compliance with Natura 2000 but non-compliance with Plaice Box regulations we set the

residual effort node to state 1. Different probabilities were assigned to grid cells outside closed areas depending on whether fishing effort was low or a grid cells was outside of a PFA or whether effort was previously medium or high or inside a PFA or buffer zone of a closure. In these latter cases we increased probabilities to state 3 and 4 of the residual effort nodes to account for the fact that fleets would either concentrate in the vicinity of the closure or relocate to PFAs or other previously fished areas. In previously unfished areas 100 % of the residual effort was set to state 1 (no fishing). CPTs with multiple parent nodes can become very long and duplicate information for certain combinations of parent node states (Fenton et al., 2016). We therefore summarised the applied decision rules in Table S3, supplementary information.

2.2.7 Protection effects

To account for potentially positive effects on biodiversity of fish inside OWFs and Nature 2000 sites other than through direct effects of fisheries exclusion, namely potential increase in abundance and community complexity stimulated by the reef effect, immigration and production and through spillover into the vicinity of the fisheries restriction areas, we introduced a protection node for each indicator that should reflect reserve effects. The protection nodes are further connected to the spatial compliance nodes of OWFs and Natura 2000 sites as well as the existing OWFs (OWF 2015 or OWF 2020 for the 2020 and 2030 scenarios, respectively). We performed a literature review of studies providing empirical evidence of changes in demersal or bentho-pelagic fish species and community structure from OWFs as well as marine reserves focusing on temperate reserves in European or North Atlantic waters. For OWFs we reviewed (Winter et al., 2010; Reubens et al., 2014; Reubens et al., 2013; Bergström et al., 2013; Krone et al., 2017; Vandendriessche et al., 2015; van Deurs et al., 2012; Wilhelmsson et al., 2006; Stenberg et al., 2015; Ashley et al., 2014; Atalah et al., 2013; Lindeboom et al., 2011) and studies of recovery in marine reserves included (Moland et al., 2013; Fernández-Chacón et al., 2015; Goñi et al., 2011; Jaworski et al., 2006; Pereira et al., 2017; Harmelin-Vivien et al., 2008; Stobart et al., 2009; Vandeperre et al., 2011; Murawski et al., 2005; Murawski et al., 2000; Gell and Roberts, 2003).

Interestingly, OWF and MPA effects were similar. All studies described an increase in overall species abundance after 2-5 years. OWF surveys focused mainly on cod, which showed a high degree of site fidelity and production in OWFs. Fewer studies showed effects for flatfish species. Generally, the longer a reserve was closed, the higher were the benefits. Increases in S and

spillover were only detected after mid to long-term closures between 8 to 16 years. The longest survey on OWF effects analysed changes after a closure of 7 years and did not find evidence for neither an increased S nor spillover.

Based on the literature review, we therefore distinguished short-term (< 5 years), mid-term (5 – 10 years) and long-term effects (> 10 years), and spillover and an increase in S would only take place in and around areas closed for more than 10 years. This was the case in the 2030 scenarios for all OWFs built until 2020 as well as for the Natura 2000 sites (Table 1). The protection nodes in the 2030 scenarios have therefore links to the Buffer zone nodes surrounding an area that has been closed more than ten years to account for spillover effects. Consequently, this link is missing in the 2020 model.

We used proportions provided by Harmelin-Vivien et al. (2008) for our long-term scenarios, who found a 10 % (x1.1) increase in species richness as well as a 30 % (x1.3) increase in species abundance in six long-term protected areas (> 10 years). Since no proportions for short or midterm effects were available from the literature, we used these values but deduced 5 % from S proportions and 10% from species abundance of cod proportions per time step corresponding to 5 % and 20 % increase in mid-term closed areas and no increase and 10 % increase in short term areas respectively (Table 1). For the CSI no empirical studies investigating changes following protection exist. However, fishing tends to target large, long-lived and late reproducing hence more sensitive species. These species are usually also of higher trophic levels, and were found to respond positively to additional biomass on OWF piles (Raoux et al., 2017). While assuming an increase of highly sensitive species such as cod within reserves and OWFs, we estimated positive effects of CSI to be between those for species abundance and S (20 %, 10 % and 5% increase after long, mid and short-term closures). Studies have mostly focused on whether spillover occurs and at which scales. We therefore had to make another assumption on the magnitude of emigration, and assumed a third of the proportional increase of indicator values within closed areas (Table 1). We applied these rules to OWFs and Natura 2000 sites only when fishermen comply with the closed areas. Non-compliance of course would hamper protection affects.

Table 1. Length of closure of each spatial management measure compared to 2015 under the tw
scenario time horizons, as well as the factors with which each indicator is multiplied in th
protection nodes.

Scenarios	Node name	Length of closure	Multiplying factor			
			CSI	Cod	S	
•	OWF 2015	mid (5 -12 yrs)	1.1	1.2	1.05	
202(OWF 2020	short (1-5 yrs)	1.05	1.1	1	
2	Natura 2000	short (2-3 yrs)	1.05	1.1	1	
	OWF 2020 & 2015	long (11-22 yrs)	1.2	1.3	1.1	
0	OWF 2020 buffer	-	1.067	1.1	1.033	
203(OWF 2030	short to mid (1-10 yrs)	1.075	1.15	1.025	
(1	Natura 2000	long (12-13 yrs)	1.2	1.3	1.1	
	Natura 2000 buffer	-	1.067	1.1	1.033	

2.3 Scenarios

We used two time horizons for our scenarios based on the two approval cycles for OWF developments, namely 2020 and 2030. Therefore the additionally closed areas in 2030 are the new OWFs only. For the protection nodes as well as for spillover of all biological indicators the above described increases were implemented for mid to long-term closures in 2030. We therefore created a buffer zone for the OWF 2020 sites in the 2030 model which will then be closed for more than 10 years and linked the protection nodes to all buffer zones to model spillover. We also assume higher rates of temperature change compared to the 2020 scenario but with same compliance rates. For both time horizons we simulated each possible combination of compliance/ non-compliance and temperature change/ no change which resulted in 8 scenario combinations (see Table 2).

Climate change will lead to multiple changes in marine ecosystems (see comprehensive review by Quante and Colijn (2016) for North Sea assessment). The projected changes, especially an increase in sea surface and bottom temperature, will modulate communities and likely favour more tolerant or warm-water species and a shift of demersal fish assemblages towards deeper waters (Dulvy et al., 2008). The German Bight shows the largest warming trend in sea surface temperature since the late 1980s compared to other North Sea areas (Meyer et al., 2011). Specifically over the period 1985 to 2006, sea bottom temperature (SBT) measured during the first quarter of the year rose by an average of 0.7 °C decade⁻¹ (Quante and Colijn 2016). For a similar period (1983 to2012), Dye et al. (2013) estimated a slower increase of 0.2–0.5 °C decade⁻¹ for winter SBT, but with considerable inter-annual variation. For the scenarios we therefore used the upper predictions of Dye et al. (0.5 °C decade⁻¹) which resulted in an increase of 0.25 °C 5 years⁻¹ for the 2020 scenarios and 0.75 °C 15 years⁻¹ for the 2030 scenarios.

2.3.1 Short-term scenarios (2020)

How will fisheries be redistributed under different assumptions of compliance with regulations and how will this affect indicator states after the implementation of Natura 2000 sites and the OWF developments until 2020 in addition to environmental change? Here, we simulate a homogenous temperature increase of 0.25 °C in all grid cells (scenario 3 & 4) as well as short term to medium-term protection effects (protection nodes) within closed areas without spillover.

2.3.2 Mid-term scenarios (2030)

How will indicator states change in space after the construction of additional OWFs and the resulting fishing effort redistribution until 2030 under different assumptions of compliance with regulations and environmental change? We simulate a homogenous temperature increase of 0.75 °C in all grid cells (scenario 7 & 8) as well as short term to long-term protection effects (protection nodes) within closed areas and spillover from OWFs that have been set up before 2020.

2.3.3 MSFD scenario

How much reduction in fishing effort from small beam trawls would be necessary to achieve good environmental status of the CSI envisioned by the MSFD until 2020? Here, we defined the CSI to be in good environmental status when any given grid cell would have a 100 % probability of being intermediately sensitive (CSI > 0.165) under assumption of no temperature increase (MSFD1) and a 0.25 °C increase until 2020 (MSFD2). We therefore added the probabilities of state 1 and 2 of the CSI node to state 3 which led to a probability of 75.2 % and 80.5 % of the CSI being in state 3 and 24.8 % and 19.5 % of being in state 4.

	OWF deve	lopment	Complia	ance	SBT i	ncrease
Scenario	2020	2030	< 100 %	100%	no	yes
1	Х		Х		Х	
2	Х			Х	Х	
3	Х		Х			Х
4	Х			Х		Х
5		Х	Х		Х	
6		Х		Х	Х	
7		Х	Х			Х
8		Х		Х		Х

Table 2. Summary of scenario components; OWF = offshore wind farms, SBT = sea bottom temperature.

2.4 BN sensitivity and performance assessment

To test the performance of our core model we removed the observations of the biodiversity indicator nodes and calculated their respective maximum-likelihood state. We then estimated the error rate by comparing the predicted most likely states of the unobserved tested nodes with the true states for the tested nodes (Marcot, 2012). Error rates can also be weighted by the total number of conditional probabilities of the respective BN if more classification error is allowed. We also computed the spherical payoff which is another measure of classification success.

We further tested model sensitivity of all biological indicators under the full scenario model for 2020 and 2030 to identify to which degree variability in posterior probability distributions is explained by other variables (Marcot, 2012).

3. Results

3.1 BN models

The core model representing the cause-effect relationship between fishing effort, biodiversity state and environmental variables in 2015 is shown in Fig. 7. It reveals that e.g. the mean CSI value across the study area is 0.169 with a standard deviation of 0.018, which is just above the threshold of 0.165 and thus representing an intermediately sensitive community. Also, there is a 47% chance to sample at least one cod (catch per 15 min trawling) in any given grid cell.



Fig. 7. Trained core BN model (status 2015) showing the main pressure-state relationships between fleet-specific fishing effort [SAR], key environmental variables and the biological state indicators.

The two models used either for the 2020 (Fig. 8) or the 2030 scenarios (Fig. 9) are shown below, both include area closure, compliance, residual fishing pressure and protection nodes of all state indicators. The model set up is almost the same, with an additional buffer zone and a link between protection nodes and all buffer zones in 2030. The configuration of model nodes (OWF sites, compliance, temperature and protection) were however adapted for each scenario. Here, we show the model configuration for scenario 1 (S1) and 8 (S8). The nodes from the scenario models show the updated posterior probability distribution of residual fishing effort and biodiversity indicators as well as the overall mean value and standard deviation across the study area. We summarised these changes for all scenario combinations by providing differences in probabilities of the lowest and highest states (e.g. state 1 and 3 for cod and state 1 and 4 for the CSI and S) as well as the mean value and standard deviation by comparing them to the probability distribution of the core model. We then used the BN probabilities to spatially predict the expected value and most probable state of the residual fishing effort and biodiversity indicators.



Fig. 8. BN model for 2020 scenarios, here showing the changes in probability distribution of indicators due to relocation of fishing effort and implementation of Natura 2000 management plans and OWF developments under non-compliance and no temperature increase (Scenario 1).



Fig. 9. BN model for 2030 scenarios, here showing the changes in probability distribution of indicators due to relocation of fishing effort and implementation of Natura 2000 management plans as well as additional OWF developments under assumption of perfect compliance and sea bottom temperature increase (Scenario 8).

3.2 Fishing effort redistribution

Probabilities of encountering the lowest state of residual fishing pressure (state 1; no fishing) significantly increased across all fleets and scenarios which was expected due to the significant area closures in Natura 2000 sites and OWFs (Table 3). Consequently, mean residual fishing pressure per grid cell decreased. Probabilities of state change between compliance and non-compliance scenarios and 2020 and 2030 scenarios (increased number of OWFs) only changed marginally. A slightly higher change from additional OWF area closures for small beam trawls and higher change due to better compliance of large beam trawls and otter board trawls was observed. However, probabilities of effectively reducing the highest state of fishing effort per grid cell were low in all scenarios (2 % to 4.1 %).

Table 3. Changes in probability distribution (percent change in lowest and highest state, as well as in
the overall mean) for each fleet under all scenarios compared to the core model (initial fishing pressure
from 2015). All positive changes indicating an improvement in state (> ±5 %, i.e. a decrease in
probability of the lowest state and an increase in the probability of the highest state and mean value)
are marked in blue.

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		2020 scenarios		2030 sc	enarios
Fleet	State & mean	1 & 3	2 & 4	5 & 7	6 & 8
		nc	с	nc	с
Small beam trawls	low	8.9%	11.3%	9.9%	12.4%
	high	-2.8%	-2.8%	-3.0%	-3.0%
mean		-25.3%	-25.7%	-26.7%	-27.1%
Otter board trawls	low	16.0%	19.5%	17.3%	21.0%
	high	-2.0%	-2.0%	-2.1%	-2.1%
	mean	-19.6%	-23.1%	-24.1%	-24.6%
Large beam trawls	low	24.9%	31.7%	25.7%	32.4%
	high	-4.0%	-4.0%	-4.1%	-4.1%
	mean	-47.4%	-49.6%	-48.1%	-50.7%

nc: non-compliance, c: compliance

Predicted residual effort maps of expected values for the 2020 scenarios with and without perfect compliance (100 % and < 100 % comp in compliance nodes) are shown in Fig 10. Effort maps for the 2030 scenarios are not presented since there are only minor differences from 2020 maps in and close to the additional OWF sites (see Fig.10, map of change 2020 – 2030). Overall fishing effort patterns did not differ significantly between 2015 and 2020. However, total effort in the unregulated areas increased significantly (35 % for small beam trawls, 18 % for large beam trawls and 44 % for otter trawls).



Fig. 10. Fishing effort for the three main international bottom trawl fleets interpolated from VMS data for 2015 [top panel] and predicted residual fishing pressure in 2020 [middle panels] after area closure of OWFs and Natura 2000 sites under the assumption of non-compliance (non-comp) and perfect compliance (comp), as well as changes in effort between 2015 and 2020 and 2020 and 2030 of each fleet. Changes are defined as being significant if they are higher than the respective standard deviation from the BN model [bottom panels]. Also shown are the area closures expected to be implemented for each time step.

For small beam trawls, effort increased particularly in previously low fished areas outside the PFA (see Change 2015 - 2020 in Fig. 10). Otter trawl effort increased especially in the PFA but also in most other previously fished areas. All strong increases in effort (> 1 SAR per grid cell) occurred in PFAs not surprisingly with the defined decision rules. Overall, areas like the

Elbe River Glacial Valley and the Eastern German Bight are likely to receive the highest proportion of redistributed fishing effort in the future. Predictions further showed that non-compliance is likely to take place in the Sylt Outer Reef for small beam and otter trawls, as well as at the Dogger Bank for large beam trawls and otter trawls. In contrast, fishing effort at Borkum Reef Ground remains low. Because it does not belong to the PFAs, non-compliance is not relevant (see 2015 map).

3.3 Changes in biodiversity state

Table 4 shows that most changes in probabilities and mean values were positive (as indicated by the blue colour) and that change was generally more pronounced for cod than for the community level indicators. As expected, the magnitude of change in comparison with the core model was stronger for the 2030 scenarios and the protection nodes in general. The only negative changes in probability were predicted for the CSI in scenarios where a temperature increase was included in the model. In contrast, the highest positive changes of other indicator values also occurred in these scenarios (scenario 3, 4, 7 & 8). Mean values of cod increased in all climate change scenarios but with little difference between 2020 and 2030 (up to 11 % and 17 % increase, respectively). Species richness was affected but showed only an up to 10 % increased probability of encountering the highest state in S. All changes in mean values were however not significant due to relatively high standard deviations; the only exception being CSI predictions of the protection node under scenario 5 and 6.

There were no or marginal difference in probability distributions (1 - 2 %) between compliance and non-compliance scenarios (e.g. S1 and S2, S5 and S6 etc.). These differences were slightly higher for the protection nodes (e.g. a 5 % increase in mean cod under perfect compliance) which was expected since additional protection effects were only realised for grid cells where fleets comply with regulations. These effects were however foiled in the climate change scenarios. The additional OWF sites also caused marginal changes in probabilities (0 - 3 %), again with slightly larger differences for the protection nodes.

We used scenario 1 and 3 to make an additional bottom-up prediction relevant to the MSFD task, *i.e.* achieving GES of biodiversity indicators until 2020 (scenario MSFD1 & MSFD2). Here, we simulated how much effort reduction of small beam trawls would be necessary until 2020 in order to achieve CSI values in any grid cell that were indicative of an intermediately sensitive community (larger or equal to 0.165). According to the model output this would require an overall reduction of mean SAR per grid cell of 9 %. This corresponded to an 8.4 %

increase in unfished surface area or number of grid cells (8.4 % increase state 1) and a 1.4 % decrease of surface area receiving > 1 SAR per grid cell. Under the assumption of a temperature increase these values were actually slightly reduced to 7 %, 7.3 % and -1.2 %, respectively.

Table 4. Changes in probability distribution (percent change in lowest and highest state) compared to the core model, as well as the overall expected mean value and associated standard deviation for each indicator under all scenarios. All positive changes indicating an improvement in state (> \pm 5 %, i.e. a decrease in probability of the lowest state and an increase in the probability of the highest state) are marked in blue, all negative state changes are marked in red; mean values that are significantly different from the core model are marked with an asterisk.

		2020 Scenarios				2030 Sce	enarios		
Indicator	State &	1	2	3	4	5	6	7	8
	mean value	nc	С	nc&t	c&t	nc	С	nc&t	c&t
CSI	low	-1%	-1%	<1%	<1%	-1%	-1%	<1%	<1%
	high	1%	1%	-5%	-5%	1%	1%	-10%	-10%
	mean value	0.17	0.17	0.168	0.17	0.17	0.17	0.166	0.166
	stdv	0.018	0.018	0.017	0.018	0.018	0.018	0.16	0.16
Protection	low	-1%	-1%	-1%	-1%	-2%	-2%	-2%	-2%
(CSI)	high	3%	4%	-2%	-2%	12%	15%	3%	5%
	mean value	0.176	0.177	0.173	0.177	0.182*	0.182*	0.177	0.178
	stdv	0.028	0.029	0.027	0.028	0.03	0.03	0.028	0.029
S	low	-1%	-1%	-2%	-2%	-1%	-1%	-4%	-4%
	high	6%	7%	8%	9%	6%	7%	9%	10%
	mean value	24.9	24.9	25.1	24.9	24.9	24.9	25.2	25.2
	stdv	2.1	2.1	2	2.1	2.1	2.1	1.9	1.9
Protection	low	-1%	-1%	-2%	-2%	-3%	-4%	-5%	-6%
(S)	high	6%	7%	8%	9%	14%	15%	16%	17%
	mean value	25.2	25.2	25.3	25.2	25.8	25.8	26.1	26.1
	stdv	2.4	2.4	2.3	2.4	2.8	2.8	2.6	2.6
Cod	low	-10%	-12%	-12%	-13%	-10%	-12%	-14%	-15%
	high	5%	5%	8%	8%	5%	6%	12%	13%
	mean value	1.46	1.49	1.51	1.49	1.46	1.49	1.58	1.59
	stdv	0.75	0.74	0.76	0.74	0.75	0.75	0.76	0.76
Protection	low	-10%	-12%	-12%	-13%	-11%	-13%	-15%	-16%
(Cod)	high	5%	9%	11%	10%	9%	10%	17%	19%
	mean value	1.58	1.65	1.68	1.63	1.65	1.69	1.81	1.84
	stdv	0.95	0.97	0.99	0.96	0.99	0.98	1	1

Scenario components: nc= non-compliance; c= compliance; t=temperature increase

While Table 4 summarises the changes in probabilities for indicator states we also spatially predicted values for all indicators and their protection nodes under all scenarios across our study grid. Predicted maps are presented for the core scenarios, scenario 1 and 8 only, to provide the biggest range of possible changes from now to 2020 and 2030 (Fig. 11).

Naturally, the biggest changes were predicted to happen in the 2030 (S8) scenario and generally, protection nodes showed larger recovery inside closed areas as well as spillover in 2030. For the CSI, Natura 2000 sites would essentially fail to protect the overall community if temperature would rise to anticipated levels (0.75 °C). Protection and spillover may however be able to buffer these negative effects locally, inside and close to reserves. Cod responded well to protection. S is also predicted to increase in Natura 2000 sites, especially in the Western part of the Sylt Outer Reef, which is similar for the CSI. This shows that both biodiversity indicators respond to the exclusion of fisheries and that compliance, affecting conservation success, can be locally different, exemplified by the fact that the western part of the Sylt Outer Reef showed high overall compliance in contrast to the eastern part. Some local increases in indicator values in new OWF sites could also be observed for all indicators in both scenarios. While the maps essentially mirror the probability changes in Table 4 they also show that predicted indicator changes were spatially inhomogeneous or more nuanced which becomes clear when looking at differences between scenario combinations (Fig. 12). For the CSI large areas of decline are shown (44 % of which 11.3 % were significantly lower than the core model). However, not all predictions in scenario 8 showed an index decline and not all changes in S were positive. In fact, the CSI increased in coastal areas and OWFs in cluster 6 -8 (total increase of 16 %), while S showed some however also not significant declines (smaller than the standard deviation of the predicted mean indicator value) in the vicinity of the Sylt Outer Reef in areas with increased fishing effort. Most of the significant changes were higher indicator values in the Dogger Bank under perfect compliance and in some areas of the Sylt Outer Reef. Fig 12 further shows local increases in indicator values when compliance is perfect (change S1 - S2) and in OWFs that will be additionally closed after 2020 (change S1 - S5). A local decrease can be observed for CSI and S in the OWF that was randomly selected to show the effects of non-compliance.



Fig. 11. Distribution maps of three biodiversity indicators, namely the CSI, species richness (S) and CPUE of cod trained with fishing effort and environmental variables from the core BN model [top panel], as well as their expected values predicted under scenario 1 (S1: 2020, non-compliance) [middle panels] and scenario 8 (S8: 2030, perfect compliance & temperature increase) [bottom panels]. Also shown are the area closures expected to be implemented for each time step.



Fig. 12. Value differences in the three indicators between several scenarios and / or the core model. Significant changes (values larger than the respective standard deviation of the predicted mean indicator value) are marked in dark red (decrease) and dark blue (increase) whereas non-significant changes are indicated in light red and blue.

3.4 Sensitivity and performance assessment

First, we assessed the performance of the core model, meaning how well the model was able to predict states of indicator values in comparison to the originally observed indicator data. The spherical payoff (ranging from 0 to 1; with 1 being a perfect classification) showed a relatively accurate classification success rate for the CSI (0.79) and cod (0.75) and reasonable values for and S (0.66). The calculation of the type I error rate for S was however high, revealing that the core model failed to predict the most likely state of an indicator in comparison to the original data in 43.5 % of all cases. Error rate were lower for cod and the CSI with values of 35.2 %, 31.8 % and 26.9 % respectively.

Fig. 13 shows a measure for mapping uncertainty of spatial predictions. It provides the likelihoods (from 0 to 1) of expected beliefs with which each indicator state was predicted, here based on scenario 1. We predicted the believe for each grid cell which is the probability of occurring state. We then chose the belief of the state which corresponds to the formerly predicted values per. For example, if S was predicted to be 23 in a given grid cell, we used the belief of state 2 which corresponds to S values of 23 - 24. The closer the value to 1 the higher the likelihood of belief with which a certain state was predicted. Beliefs are highest for CSI and lowest for S which is in accordance with the classification success previously discussed. Generally, high and low states were predicted with higher beliefs.



Fig. 13. Likelihood of the believe with which indicator states were predicted per grid cell and mapped for scenario 1.

Table 5 shows the results of the sensitivity assessment as variance reduction for each of the indicators. Here we only list assessment results for the 2020 model, since variance reduction was practically identical between the 2020 and 2030 models. Cod and S were more influenced by residual fishing pressure than the CSI, the latter mostly depended on depth and/ or bottom

temperature. Generally, indicators were only marginally influenced by spatial compliance and area closures (< 2 % to 3 %) with all OWF sites accounting for less than 1 %.

Node	Variance reduction			
	CSI	Cod	S	
Residual effort	2.9%	12.5%	10.9%	
Trawling	2.1%	3.7%	5.5%	
Plaice Box	-	2.3%	-	
Spatial compliance (Plaice	-	3.0%	-	
Box)				
Natura 2000	< 2%	< 2%	2.2%	
Spatial compliance (N2000)	< 2%	< 2%	2.4%	
OWF 2020	<1%	< 1%	< 1%	
Spatial compliance (OWF	< 1%	< 1%	< 1%	
Depth	11.4%	-	-	
Bottom temperature	8.7%	2.6%	5.7%	
Sediment	< 2%	3.6%	2.0%	

Table 5. Sensitivity assessment of all indicators to BN nodes.

4. Discussion

The aim of this study was to develop a BN using the main cause-effect pathways to explore risks and uncertainties of future ecosystem-based spatial management measures on fish biodiversity. We tested two levels of OWF developments in combination with Natura 2000 sites and existing spatially managed areas with different assumptions in relation to compliance, protection effects and climate change (in the sense of temperature increase). Main findings include that displacement of fishing effort did not lead to any significant decline in biodiversity indices at the EEZ scale and effects of area closures were most prominent around closure. EEZ wide effects were only caused through a simulated temperature increase.

4.1 Results and quality of predictions

BN predictions denoted areas where indicators potentially recover due to the exclusion of fisheries and also demonstrated that non-compliance could hamper recovery. For some indicators local increases around OWFs and Natura 2000 sites were revealed. These increases were partially dependent on depth and temperature. The 2030 scenarios indicated spillover effects due to the decision rules specified in the BN as well as local deterioration of indicators

due to fisheries displacement to the vicinity of area closures. Overall, the scenarios draw a rather optimistic picture where in almost all cases probabilities of a low indicator state decreased, which means that an improvement of the ecological status in terms of fish biodiversity can be expected.

Temperature increases had the biggest influence on all indicator values since it affects the entire study site equally. However, responses were not linear. The CSI e.g. showed a decline in many areas where temperatures were above 10.5 °C (state 3), whereas values increased in coastal areas to state 2. Contrary to that, the only significant decrease in value was detected in the northern part of the EEZ where temperatures were consistently below 10.5 °C even under scenario 8, and may be attributable to deeper water depths. Recovery of S after fisheries exclusion of the Sylt Outer Reef under scenario 1 occurred only in the western part, which showed temperatures between 9.5 and 10.5 °C (state 2). In scenario 8, where temperature increased 0.75 °C, the eastern part recovered as well to state 2. However, this was also one of the areas where the probability of prediction of S was low. Surprisingly, in the climate change scenarios the cold water species cod, that e.g. prefers spawning areas between 7-9 °C (González-Irusta and Wright, 2016) recovered as well, and abundance increased significantly across the Dogger Bank. This may have been due to the fact that the temperature node explained only a small amount of total variability (2.6 %). Another reason could be that juvenile cod, which make up the majority of catches in the GASEEZ survey, are less vulnerable to increases in temperature than adult individuals (Rindorf et al., 2008).

The protection nodes of each indicator were indicative of positive changes, resulting from assumptions that indicators can increase in and around closed areas. While the assumptions were based on literature information, empirical evidence of longer-term effects from OWFs is still lacking. Short-term local increases may be also due to attraction from surrounding areas rather than increased production. In addition, the shape of the functional response to recovery over time inside a closed area is not known yet. For the protection nodes we assumed a linear increase as well as equal response to Natura 2000 sites and OWFs which may not be accurate. Conservation benefits of OWFs were emphasised frequently and were also used as advocacy for green energy development (Wilhelmsson, 2010). Some authors even suggested that OWFs are more effective than marine reserves in protecting biodiversity (Hammar et al., 2016) and to date, the number of studies describing positive changes inside OWFs outweigh the negative. However, OWFs can also cause harm to fish. Empirical studies showed decreases in fish abundance during the construction phase (Bergström et al., 2014), but due to mobility

species returned after construction ended (van Deurs et al., 2012). Other adverse effects, such as the influence of electro-magnetic waves from cables and OWF structures, could impact species with electro-magnetic receptors such as elasmobranchs and eels (Öhman et al., 2007). Sharks and rays in the German EEZ mostly occur along the Duck's bill where no OWFs will be developed in the future. However, large scale OWF developments along other parts of the Dogger Bank could endanger these species. Other negative effects such as noise pollution and resulting changes in health and communication of species are less well understood, but studies suggest limited impact (Bergström et al., 2013; Petersen and Malm, 2006). The BN could however be easily adjusted when additional information is available. We assumed spillover up to 10 km from Natura 2000 sites which is the same distance that we chose for fishing effort relocation from closed areas. This was a compromise between studies suggesting that spillover mostly occurred on very local scales (up to 1 km) (Halpern et al., 2009) and studies suggesting effects up to tens to hundreds of km (Gell and Roberts, 2003). To summarise, the protection nodes represent current best evidence but are also prone to a high uncertainty.

In the past, fishing effort relocation was often modelled at too large a scale (ICES rectangle) to be useful for local assessments in relation to MSP (Hiddink et al., 2006a; Simons et al., 2015). Our grid cell size of 5 x 5 km was a good compromise between the resolution of data sources and the demands of the MSP process. Effort maps showed that overall fishing patterns of the three fleets did not change for any of the scenarios, while fishing effort significantly increased in PFAs, which are not closed to fishing. This was due to the relatively conservative decision rules, which we incorporated into the CPTs of the residual effort nodes, i.e. we did not allow fishers to move to previously unfished areas. This could have underestimated negative impacts on fish because unfished communities may be less adapted to fishing mortality (Greenstreet et al., 2009). However, even though trawling effort is patchy, truly unfished areas hardly exist. Furthermore, we did allow for redistribution to low-fished areas. Due to this parameterisation, particularly small beam trawls increased their effort further offshore in the scenarios, which could mean that they would exploit different resources in the future.

Our analysis further suggests that while the total area loss due to Natura 2000 sites and OWFs is substantial (28 %), major fishing grounds are only marginally affected by area closures. The large beam trawl and otter trawl fishery will be most affected by the implementation of OWFs and Natura 2000 sites, respectively, but because the latter is a mixed fishery there may be more potential to relocate to other areas (Slijkerman and Tamis, 2015). In contrast, the shrimp fishery with small beam trawls is highly specialised but also least affected by future

area closures. Slijkerman and Tamis (2015) suggest that the more specialised a fishery is, the harder it is to predict how fishing effort will be displaced. Contrary to this, relocation could in fact be easier to predict due to clear distributions of target resources.

The precise quantification of relationships between fishing pressure and biodiversity state from absolute values has often failed in the past. Here, we showed that all biodiversity indicators declined with increasing fishing pressure into relative states. A relative assessment of cause and effect by binning values into discrete states as it is done in a BN may therefore be a practical way to quantify these relationships. For example, S showed high sensitivity to the (residual) effort node although a clear mechanistic understanding has been lacking. The setting of states has a major influence on overall model performance and thus needs to be carefully gauged to avoid spurious relationships (Uusitalo, 2007).

Further, S estimations also showed the highest uncertainty (the lowest spherical payoff and highest error rate), which was caused by the large scatter of the raw data (Fig. S1). Furthermore, the predictions from the core model truncated the data range (Fig. S3, supplementary information) by excluding values from state 1 (20 - 22 species) due to its relatively low probability in the model. This resulted in a continuous reduction of S with increasing fishing effort, which did not accurately represent the original structure in the data. For these reasons S predictions have to be interpreted with caution. The inherent structure in the data was best preserved for the CSI and cod, which also showed the highest predictive power. While classification success (error rate and spherical payoff) was best for CSI, cod showed error rates of about third. However, their spherical payoff was still reasonable, which means that predictions of CSI and cod can be used with more confidence in a decision making context.

4.2 Caveats of the models

The spatial models of biodiversity indicators, parameterising the BN, represent multi-annual average distributions derived from fisheries surveys performed in 2005, 2009 and 2013 in the fourth quarter of the year. For fishing effort we used the most recently available information from 2015. Due to the fact that the data sources temporally do not overlap, we can only interpret relative risks. Still, the model was able to predict spatially explicit fleet- and species-specific responses.

Our analysis of fishing effort redistribution was based on the primary fishing gear, because international logbook data were not available to define the actual métier. Therefore, a certain amount of fishing activities may be misclassified, e.g. small beam trawls operating beyond the traditional fishing grounds of the shrimp fishery likely target flatfish, whereas some of the otter board trawlers in coastal areas may actually target brown shrimp. While the analysis would benefit from a higher métier level, the redistribution patterns of fleets are still indicative of the effects that need to be expected following fisheries closures.

As already mentioned in the method section, the established links between each indicator and the fishing fleets were either based on empirical knowledge as was the case for the CSI or based on scatterplots. For the latter we chose the relationships that represented the highest degree of change (decline in indicator value with increases in fishing pressure) to be useful in a management context. This led to cod being linked to large beam trawls instead of otter board trawls which are the main fishing fleet for cod. In a fisheries management context this would not be useful. However, since we are here interested in the ecosystem or biodiversity context, pressure from other fleets then the target fleet are also of importance. In addition, cod is only a bycatch species in the German EEZ and most of the sampled cod in the GASEEZ survey is below minimum conservation landing size and therefore not specifically targeted by large beam trawls.

Potentially the largest limitation of a BN in an environmental modelling context is the inability to include feedback loops between nodes (Uusitalo, 2007). The distribution of fishing effort is naturally driven by the distribution of the target species. In our model, the relationship is however top-down and not interactive as it is e.g. the case in a recent fishing reallocation model (DISPLACE) (Bastardie et al., 2014). The strength of the BN lies rather in representing various ecosystem components and by incorporating uncertainty into the performance of management measures in a way that allows consideration of the precautionary principle.

4.3 BNs to support MSP & conclusions

Based on our findings and keeping assumptions and limitations in mind, we conclude that no large scale EEZ wide effects on fish biodiversity are expected due to area closures and fisheries displacement. Results from scenarios considering additional temperature increases however stress that climate change may throw a curve ball by inducing change that could override management actions and make it difficult to reach targets of GES (Lynam and Mackinson, 2015; ICES, 2013). On the other hand positive effects may occur for warm-water species, thus buffering a certain level of increased fishing effort. While temperature effects are more straightforward to forecast at the species level, predicting community changes is more challenging.

Our proposed model represents the initial step to set up a comprehensive management model based on current knowledge. In addition, our scenarios aimed to mimic a spatial management process such as the German MSP, spanning across different time scales in contrast to other long term scenario assessments. Future knowledge and information can be easily integrated, e.g. on long-term effects of OWFs and on Nature 2000 sites. Other future spatial fisheries measures such as real time closures (temporally protected areas), which are an additional measure proposed by the CFP reform (European Parliament, 2015) could also be incorporated into the model. Furthermore, the protection of spawning grounds should be integrated into MSP procedures (Janßen et al., 2017); e.g. for cod (González-Irusta and Wright, 2016) certain areas in the German Bight were identified as recurrent spawning grounds. Spatial management under the German MSP delineates priority areas for various uses, not just OWF developments. Effects of other uses such as aggregate mining were not included in the current model. However, a BN model could be developed to include the full suite of spatial management measures. The great flexibility in model structure and especially the ability to integrate management measures at different temporal and spatial scales make it extremely useful in a MSP context.

In conclusion, the presented model aims to reflect a holistic assessment of the management system in place that allows the integration of different spatial management options under various policies and their combined effects on marine fish biodiversity. We were able to spatially predict in which of the OWF and Natura 2000 sites recovery would be more likely. The model could therefore be used in tactical decision making, e.g. in the environmental assessment of developing a certain OWF cluster. In conclusion, the combination of BNs and GIS is a very useful framework for ecosystem-based spatial assessments, and the model structure potentially facilitates the integration of policy and science.

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Supplementary data

Node	States	Description
Large beam	0;	Mean fishing effort in 2015 expressed in swept area ratio
trawling;Small beam	0 - 0.15;	(SAR) per grid cell (5 x 5 km) of the international large beam
trawling;	0.15 - 1(0.7);	trawl fleet (> 221 kW), small beam trawl fleet (< 221 kW) and
Otter trawling	> 1(>0.7)	otter trawl fleet
Residual effort	0; 0 - 0.15;	Remaining fishing effort in scenarios after Natura 2000
	0.15 - 1;	fishing restrictions have been implemented and additional
	>1	OWFs are being developed
Principle fishing area	inside; outside	Fishing ground where each fleet exerts 75% of its total effort calculated after (Fock, 2008) based on data from 2012 - 2015
Nature 2000;	inside;	Each grid node either falls inside or outside an area where
OWF	outside	specific fishing regulations apply: the Plaice Box, OWFs
2015/2020/2030;		(baseline and future scenarios) and Natura 2000 sites
Plaice Box		(different regulations apply to small beam trawlers and other
		bottom trawling activities)
Compliance	Noncomp (non-	Compliance of fishing fleet with fishing restrictions;
	compliance);	compliance for the Plaice Box and existing OWFs were
	Comp (compliance)	calculated empirically from VMS pings. Compliance for future OWF and Natura 2000 closures was estimated
Spatial compliance	Outside:	Spatial representation of state across study area outside refers
Spatial compliance	Comp.	to outside a closed area comp and noncomp refer to the
	Noncomp	compliance with each closed area
Buffer	Inside	Δ 10 km buffer was generated in ArcGIS 10.3 around OWEs
Duitei	outside	and Nature 2000 sites
Community	0.13 - 0.145	Index that expresses a demersal fish communities' sensitivity
sensitivity index	>0.13 - 0.143,	to fishing mortality. The index is weighted by abundance and
(CSI)	>0.145 -0.155,	is based on species specific trait information (ultimate body
(CDI)	>0.155 -0.105,	length growth parameter k length and age at first maturity)
	>0,105 -0.185,	CSI mans were taken from Pambo et al. (in press)
Protection (CSI)	>0.103 - 0.21	An increase in CSI values was assumed for both 2020 and
Tiolection (CSI)	0.13 - 0.143,	2020 scenarios within OWEs and Nature 2000 sites as well as
	>0.145 -0.155,	2050 scenarios within Owrs and Natura 2000 sites as well as in their vicinity (10 km huffer)
	>0.155 -0.105,	in their vicinity (10 km burler)
	>0,105-0.185,	
Cod	>0.103 - 0.21	Intermalated actab per 15 min traviling of and was taken from
Cou	0, 1, >1	Bamba at al (in press) based on CASEEZ data from
		Rambo et al. (III press) based on GASEEZ data from
Ductastian (Cad)	0, 1, 5, 1	An increase in CSI values was assumed for both 2020 and
Protection (Cod)	0; 1; >1	An increase in CSI values was assumed for both 2020 and 2020 generics within OWEs and Nature 2000 sites as well as
		2050 scenarios within OWFs and Natura 2000 sites as well as
C	20 22 22 24	In their vicinity (10 km buller)
S	20 - 22; 22 - 24;	Indirectly mapped species richness (number of species) from
	24 - 26; 26 - 28	Rambo et al. (in press)
Protection (S)	20 - 22; 22 - 24;	An increase in S was assumed for the 2020 scenarios within
	24 – 26; 26 - 28	OWFs and Natura 2000 sites and for 2030 scenarios as well as
-		in their vicinity (10 km buffer)
Temperature	7 – 9.5; 9.5 – 10.5;	Mean December bottom temperature [°C] in 2015 from
	10.5 - 11.2	Nunez-Riboni and Akimova (2015)
Depth	4 - 25; 20 - 35;	The average depth [m] for each grid cell was derived from the
	30 - 45; 40 - 72	German Federal Maritime and Hydrographic Agency
a 11	aa a -	(www.bsh.de)
Sediment	tS: fine sand; mS:	Sediment data were obtained from the German Federal
	medium sands; M:	Maritime and Hydrographic Agency (www.bsh.de) with 4
	muds; cS: coarse	sediment categories. Each grid cell was categorised according
	sediment	to the dominant sediment category

Table S1. Overview of BN model nodes, node states and description	of data sources
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Offshore wind farms	Safety zone
	Implementation
Alpha ventus	26 July 2008
BARD Offshore 1	01 May 2009
Trianel Windpark Borkum	26 August 11
Nordsee Ost	01 July 2012
GlobalTech I	01 July 2012
Meerwind Süd/Ost	01 August 12
DanTysk	01 December 2012
Amrumbank West	15 May 2013
Borkum Riffgrund 1	01 August 13
Butendiek	01 March 2014
Gode Wind 01	01 January 2015
Gode Wind 02	01 January 2015
Sandbank	02 April 15
Nordsee One	02 October 2015

Table S2. Dates of implementation of safety zones in and 500 m around the construction sites of each OWF in the German EEZ of the North Sea between 2008 and 2015 (Data: pers. comment, BSH).



Fig. S1. Mean annual distribution of fishing effort [swept area ratio; SAR] from 2010 to 2015 (top to bottom) for the three main international bottom trawl fleets (small beam trawls, otter trawls, large beam trawls; from left to right) interpolated from VMS data. Relevant areas closed in each of the respective years (Plaice Box and OWFs) are superimposed.



Fig. S2. Empirical relationship between the biodiversity indicators and their respective parent nodes: small beam trawling, large beam trawling and otter trawling (from top to bottom), sea bottom temperature (SBT) and sediment (M: mud, fS: fine sands; mS: medium sands, cS: coarse grained sands). The red line is a loess smoother based on locally weighted regression; the dotted dark red lines indicate the state bins of the respective BN nodes.



Fig. S3. Inferred relationship between the trained biodiversity indicators and their respective parent nodes from the core model: small beam trawling, large beam trawling and otter trawling (from top to bottom), sea bottom temperature (SBT) and sediment (M: mud, fS: fine sands; mS: medium sands, cS: coarse grained sands). The red line is a loess smoother based on locally weighted regression; the dotted dark red lines indicate the state bins of the respective BN nodes.
Fishing effort [SAR]	PFA	Spatial Compliance		Buffer		Residual effort [SAR]				
		Natura 2000	OWF	Plaice box	Natura 2000	OWF	0	0 – 0.15	0.15 – 1	>1
0	0	0	0	0	ΙUΟ	ΙUΟ	100	0	0	0
(none)	Ι	0	0	0	ΙUΟ	ΙUΟ	95	5	0	0
	ΙUΟ	NC U O	$NC \cup O$	$NC \cup O$	$I \cup O$	ΙUΟ	0	100	0	0
	ΙUΟ	$C \cup O$	CUO	CUO	$I \cup O$	ΙUΟ	100	0	0	0
0 - 0.15	0	0	0	0	$I \cup O$	ΙUΟ	5	95	0	0
(low)	Ι	0	0	0	$I \cup O$	ΙUΟ	0	95	5	0
	Ι	NC	$NC \cup O$	$NC \cup O$	$I \cup O$	ΙUΟ	0	95	5	0
	0	NC	$NC \cup O$	$NC \cup O$	$I \cup O$	ΙUΟ	0	100	0	0
	ΙUΟ	NC U O	NC	$\mathrm{NC} \cup \mathrm{O}$	$\mathrm{I}\cup\mathrm{O}$	ΙUΟ	0	100	0	0
	ΙUΟ	NC U O	NC U O	NC	ΙυΟ	ΙUΟ	0	100	0	0
	ΙUΟ	$C \cup O$	CUO	CUO	$I \cup O$	ΙUΟ	100	0	0	0
0.15 - 1(0.7)	0	0	0	0	$O \cup I$	$O \cup I$	0	5	95	0
(med)	Ι	0	0	0	0	0	0	5	90	5
	Ι	0	0	0	$O \cup I$	$O \cup I$	0	3	90	7
	Ι	0	0	0	Ι	Ι	0	0	90	10
	$O \cup I$	0	NC	0	$\mathrm{I}\cup\mathrm{O}$	ΙUΟ	0	100	0	0
	$O \cup I$	0	0	NC	ΙυΟ	ΙUΟ	0	100	0	0
	Ι	NC	O U NC	$O \cup NC$	ΙυΟ	ΙUΟ	0	80	20	0
	0	NC	O U NC	$O \cup NC$	ΙυΟ	ΙUΟ	0	90	10	0
	$O \cup I$	$C \cup O$	$C \cup O$	$C \cup O$	ΙυΟ	ΙUΟ	100	0	0	0
> 1 (0.7)	0	0	0	0	0	0	0	0	20	80
(high)	0	0	0	0	0	Ι	0	0	15	85
	0	0	0	0	Ι	0	0	0	15	85
	0	0	0	0	Ι	Ι	0	0	10	90
	Ι	0	0	0	0	0	0	0	10	90
	Ι	0	0	0	$O \cup I$	$O \cup I$	0	0	5	95
	Ι	0	0	0	Ι	Ι	0	0	0	100
	$O \cup I$	0	NC	0	$I \cup O$	ΙUΟ	0	98	2	0
	$O \cup I$	0	$\mathrm{NC} \cup \mathrm{O}$	NC	ΙυΟ	ΙUΟ	0	90	10	0
	Ι	NC	O U NC	O U NC	$I \cup O$	ΙUΟ	0	70	30	0
	0	NC	O U NC	O U NC	ΙυΟ	ΙUΟ	0	80	20	0
	O∪I	CUO	CUO	CUO	$I \cup O$	ΙυΟ	100	0	0	0

Table S3. Decision rules applied to the Conditional Probability Table of all residual pressure nodes. The Plaice Box parent node is only connected to large beam trawling activities; SAR values in brackets represent large beam trawls.

I = inside; O = outside; NC = non-compliant; C = compliant; U = OR; OWF: offshore wind farm; PFA: principle fishing area. In cases where combinations of parent nodes per grid cell are mutually exclusive such as compliance of Natura 2000 and non-compliance in Plaice Box we set the Residual pressure node to the lowest state (SAR = 0).

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Chapter 6

General discussion

Achieving sustainable development by facilitating conservation of biodiversity and the marine environment and simultaneously intensifying and diversifying maritime activities has been the latest policy focus in Europe. The Marine Strategy Framework Directive (MSFD) and the Maritime Spatial Planning Directive (MSPD), both aiming at implementing an Ecosystem-Based Management (EBM) shall facilitate this (Gilbert et al. 2015). However, the operationalisation of these policies by implementing Ecosystem-Based Marine Spatial Management (EB-MSM) poses great challenges to the responsible management authorities, still used to single-sectoral or single-species management (Cormier et al. 2017). Likewise, information requirements for EB-MSM are highly complex. Essential gaps are operational and spatially explicit biodiversity indicators with reference targets to assess risks and tradeoffs in order to integrate different policy objectives, hampering an integrated assessment of risks on demersal fish communities.

These gaps provided the motivation for this thesis and led to the following three research questions:

- 1. How can community-level biodiversity indicators best be represented spatially to provide information in an EB-MSM context?
- 2. Can a community-level biodiversity indicator be operationalised to link changes in biodiversity state to fishing pressure?
- 3. What are the likely risks of integrating Blue Growth and conservation objectives on fish biodiversity and the vulnerability of benthic communities in the German Bight?

These research questions were subsequently addressed in the previous chapters. The methodological comparison presented in **Chapter 2** of two dominant mapping approaches revealed that modelling species distributions first and subsequently calculating index values per unit area (indirect approach) provided more useful information to represent community-level biodiversity. The comparison was performed using taxonomic biodiversity indices (species richness (S), Hill's N₁) as well as the here developed Community Sensitivity Index to fishing (CSI). The CSI was designed to be sensitive and responsive to fishing pressure by incorporating life-history traits which indicate how susceptible a species is to additional

fishing mortality. Its capacity to quantify pressure-state relationships with bottom trawling was tested in Chapter 3. A suite of regression-based techniques revealed significantly lower index values in areas with high fishing pressure of the coastal small beam trawl fleet. The CSI could thus be operationalised for this fleet. Responses in other areas or with other fleets were less clear or even reversed and mostly driven by environmental factors such as depth. Results stress the difficulty in quantifying precise pressure-state relationships in a chronically disturbed system and hint to risk-based approaches that look at relative rather than absolute changes. In Chapter 4 an established risk assessment framework was applied to the case study area to spatially quantify the risk of fishing effort displacement due to Offshore Wind Farm (OWF) developments onto the vulnerability of the benthic community. This was described by a Disturbance Index (DI) defined as a ratio between relative local mortality by demersal trawling fleets and recovery potential of benthic communities. The risk analysis was conducted by coupling a Bayesian Belief Network (BN) with a Geographical Information System and suggested a minor worsening in DI values. Finally, in Chapter 5, a similar approach was applied to test effects of OWFs and Marine Protected Areas (MPAs) as well as resulting fishing effort displacement to explore associated risks and uncertainties on fish biodiversity (CSI, S & abundance distribution of cod). Scenarios incorporated amongst others fishermen compliance, protection effects of MPAs and temperature increases to mimic climate change. Results revealed that conservation effects through area closures outweighed negative effects from the relocation of fishing effort. Nevertheless, non-compliance could locally hamper recovery. EEZ wide effects were only caused through a simulated change in temperature and suggest likely increases in species richness and abundance of cod and significant decline in CSI.

Based on the three research questions this chapter synthesises results, discusses strength and weaknesses of the methodologies used and defines future research and data needs. Taken together, the results of this thesis allow some indications on the level of risks that fish biodiversity and the vulnerability of benthic communities is likely to face in the German Bight. Further, institutional barriers and scientific limitations to operationalise the EB-MSM approach are discussed.

1. How can community-level biodiversity indicators best be represented spatially to provide information in an EB-MSM context?

1.1 Mapping biodiversity indices

As we move towards EB-MSM, spatially explicit information on key ecosystem components are crucial. The mapping of community-level biodiversity indicators showed that there are several conceptual and technical issues pertaining to each of the two mapping approaches. Directly interpolating index values from the sampling stations assumes that catch is an adequate representation of the truth whereas many studies have shown that species diversity is inherently dependant on sample size underestimating actual diversity due to different catchabilities of less abundant species (Gotelli & Chao 2013; Gotelli & Colwell 2001; Magurran 1988). Despite these issues being widely published, studies still often neglect to address this, which has led to insensitive metrics that failed to detect real differences in diversity (Boulinier et al. 1998; Soetaert & Heip 1990). Consequently this has contributed to diversity metrics failing the sensitivity criteria for an operational indicator (Greenstreet & Piet 2008). In contrast, these issues were addressed in the indirectly modelled maps by applying the newly developed mean value approach. This approach enabled to include a range of rare species that could otherwise not have been modelled due to zero-inflation of data. Still, the effect of removing singletons or doubletons (species that occurred only once or twice throughout the survey) needs further exploration (Ferrier 2002; Granger et al. 2015). However, omitting these species had no bearing on final index values. The indirect approach further provides additional information through species distribution maps. This led to the conclusion, that the indirect approach is favourable to inform decision makers in a European policy context. The different biodiversity patterns depicted by S, Hill's N1 and the CSI reaffirm the fact that an indicator suite is needed even within the community level to assess biodiversity state. An overlay of map outputs of the three indices further indicated that biodiversity hot-spots with regards to demersal fish would not be well conserved under the future Natura 2000 network.

1.2 Future needs to provide information in an EB-MSM context

Spatially explicit community-level biodiversity indicators could facilitate the integration of biodiversity conservation into MSP processes and therefore balancing Blue Growth with conservation objectives. The current single-species focus of the MSFD monitoring programmes does not adequately describe biodiversity. They should thus be considered in the

revision of descriptor 1 (ICES 2016a). To make these indicators more reliable and useful for monitoring however requires protocols on standardisation of index calculation, data treatment, and how to adequately address sampling issues. The proposed mean value approach may provide a potential solution. The fact that spatial patterns in Hill's N1 were largely driven by a few highly abundant species could foster the argument to focus the monitoring specifically on these species to be cost effective. This would however shift focus to well adapted species of no conservation concern; and again, monitoring single species without acknowledging community patterns does not suffice in an EBM context. They should thus be considered in addition to current species-level indicators.

2. Can a community-level biodiversity indicator be operationalised to link changes in biodiversity state to fishing pressure?

2.1 Results and lessons learned

The question which community level biodiversity indicators could be operationalised in a pressure-state framework to show the impact of fishing is not new and has instigated a lot of research. Still, it has not fully been answered. Two different approaches were used in this thesis to explore and operationalise pressure-state relationships between bottom trawling and several biodiversity indicators to inform risk evaluation. First, a more traditional approach was employed by using correlation and subsequent regression-based techniques. In the second approach, BNs were used to analyse pressure and state relationships between environmental drivers, bottom trawling and a range of biodiversity indicators. The latter is discussed in the next section.

The selection criteria (chapter 1) that biodiversity indicators have often failed to fulfil in the past are specificity and responsiveness to fishing pressure (Link et al. 2010). Hence, the CSI was developed to establish a direct ecological link towards the pressure that is being managed to satisfy these criteria. This stresses the importance of hypothesis-driven in contrast to purely data-driven analyses. The hypothesis was that fisheries target slow-growing, long lived and late reproducing fish, leading to a low abundance of such traits in areas with high fishing pressure. The trend in the CSI versus combined fishing pressure from all bottom trawl fleets did not support the hypothesis beyond doubt, even though the overall trend was declining. Stable relationships were observed in several areas in the German Bight showing no decline in index value despite high levels of fishing pressure. These areas are all historic fishing grounds, providing evidence that environmental conditions are particularly favourable if

fishing could be sustained for more than one century. Further, comparing these areas with patterns in S (chapter 2 & 5) showed that these areas are lower in S. This hints to the fact that fishing may have removed entire species. However, without historical data this cannot be tested. When compared at the fleet level, the pattern was clearly discernible into different fleet specific responses while a strongly positive correlation between depth and the CSI became apparent with higher CSI values in deeper waters. Combined trawling effort disaggregated into different habitat types further showed that anticipated patterns were most apparent in coastal areas where total effort was highest. The interpretation of results was therefore complicated by a strong habitat selectivity of bottom trawls and correlation between trawl activity and depth-related community sensitivity to fishing. These issues are now emerging as pressure and state analyses are put in a broader ecosystem context (Farriols et al. 2017; Pommer et al. 2016). In addition, Classification And Regression Tree (CART) and Generalised Additive Model (GAM) analyses showed that environmental factors explained more variability in the CSI than fishing pressure from otter and large beam trawls. In contrast, fishing effort from the small beam trawl fleet and the factor depth both explained approx. 25 % each in CSI patterns.

Two key lessons were drawn from this. The first lesson pertains to the influence of habitat and natural disturbance on structuring the community. The German EEZ of the North Sea, much like other marine areas in the Southern North Sea, features a rather homogenous habitat with similar sediments and no dramatic environmental gradients in contrast to the coastal intertidal zone. Still, regression analyses showed that environmental factors had an overall stronger effect than fishing pressure. Earlier studies that looked into effects of trawling on biodiversity where almost exclusively temporal and habitat effects were not included (e.g. Greenstreet et al. 1999; Jennings et al. 1999). Therefore, these issues never came up. Given that they were based on simple correlation only, inference should be drawn with caution.

Secondly, autocorrelation between high abundances of target species (here species that have a high sensitivity index) and high levels of fishing effort due to fishermen knowledge of the main distributions of these species is a recurrent issue. A potential method was proposed to remove this trend if fishing effort is orthogonal to the distribution of the state indicators (pers. comm., Sven Kupschus, CEFAS). Generally, this presents a circular issue that is very similar to the Large Fish Indicator (LFI), even though being one of the few operationalised indicators in an EU policy context (pers. comm., Simon Greenstreet, Marine Scotland). The LFI describes the proportion (by weight) of the fish community that is larger than 40 cm

(threshold for the North Sea) (Greenstreet et al. 2011). Given that fishermen target large individuals this may conceal patterns at the community level.

To summarise, while the CSI showed some promising patterns in coastal areas and for small beam trawlers, issues remain in generalising results. The analysis further exemplified opportunities and pitfalls of operationalising community level biodiversity indicators in a pressure-state framework in chronically disturbed areas. Many of the drawn conclusions are however true for other ecological indicators as well. While there is no doubt that fishing has detrimental effects on fish community structure, a clear understanding of the functional relationship between both components remains challenging. Such an understanding can most likely only be gained through historical data analysis of spatial patterns over time. The German Autumn Survey of the Exclusive Economic Zone (GASEEZ) dataset used for the analysis would not allow such an assessment given that it only started in 2004. International Bottom Trawl Survey (IBTS) data could at least provide some insights although the much coarser spatial resolution could not uncover finer scale changes.

Over one hundred years of industrial fishing have taken their toll and likely altered the Southern North Sea to such an extent that sensitive species and habitats have been decimated; potentially with them the additional functional roles they played in the ecosystem. The remaining community may be adapted to current levels and thus to see clear changes, e.g. due to managament interventions against a backdrop of natural variability and variability in recruitment processes as well as abundances magnified through fishing is difficult (Anderson et al. 2008). Therefore, the effect size also presents a challenge. This would require huge amounts of additional survey data which wouldn't be cost effective and also too invasive. The same issue has also been found when assessing effects of new activities (OWF) in areas of high natural disturbance where potential signals from OWFs were simply lower than from natural variability (Atalah et al. 2013).

2.2 Operationalisation of biodiversity indicators: Possible solution & food for thought

Where do we go from here? Can an indicator only be operational in an EB-MSM context, if a specific pressure-state relationship can be identified? It could be argued that this leads to a limited view of what management and planning needs. Also, given that most ecological indicators and not just biodiversity indicators fail to meet criteria of being specific and responsive to one particular pressure with low responsiveness to others may just be unrealistic to attain in a multi-use area with a multitude of pressures. Shephard et al., (2015) make a strong case for surveillance indicators for which a precise relationship with anthropogenic

pressures does not have to be known. These indicators are "not only expected to directly track state in relation to GES, but also to provide complementary information (including warning signals) that presents a broader and more holistic picture of state." In the frame of this thesis the main use for indicators was to be used to test risk by means of BN scenarios. A probably more common use and requirement of the MSFD is in the frame of monitoring e.g. to track yearly change. Annual distribution maps with a measure of change per grid cell could be useful to track change in biodiversity indicators for the purpose of surveillance because any significant change irrespective of the direction of trend requires management attention. These indicators can be used in conjunction with operationalised indicators.

It could also be argued that it is the scientist's job to push the boundaries of knowledge. Therefore, there is still a great need for dedicated experimental studies to attempt to quantify pressure-state relationships. These studies have to be designed to allow extrapolation of results to larger areas (Ellis et al. 2014). However, a challenge in the German Bight will be to find adequate reference areas that have not been fished but still exhibit similar environmental features to be able to generalise results.

Biodiversity science has not been fully integrated into fisheries research (Thrush et al., 2015), with the result that a functional theory of fish community biodiversity has not been properly developed (Greenstreet, 2008). In other words, taxonomic indicators were not designed to be sensitive and responsive to fishing pressure. Given that trawling is size selective, it can be distinguished between direct effects on fish above legal catch sizes and indirect effects on small-bodies species likely not being retained in the net. Such a size structured approach is currently developed in the ICES Working Group on Biodiversity (ICES 2016a). Specifically, this approach is based on the productivity of fish species in different size-classes. Life-history traits of individual species will determine their capacity to sustain a certain level of biomass removal from fishing within a size-class (Greenstreet et al. 2012). Slow-growing species will eventually disappear from the larger size classes due to their intrinsic productivity rates becoming too low to sustain certain levels of fisheries removal. As a result, species richness could diminish in large size classes even at low levels of exploitation. In contrast, this should increase diversity in small size-classes through the removal of large piscivores, leading to a trophic cascades and prey release. These interactions will likely differ for the piscivoresdominated northern North Sea and the benthivores-dominated southern North Sea fish community. In any case, a critical issue for this type of assessment is the choice of robust thresholds to distinguish size classes in the absence of catch curves for non-target species.

3. What are the likely risks of integrating Blue Growth and conservation objectives for fish biodiversity and the vulnerability of benthic communities in the German Bight?

3.1 Risk evaluation with the help of Bayesian Belief Networks

Experts worldwide advocate the need for a more holistic consideration of all key ecosystem components that includes human activities within the ecosystem approach. However, the practical implementation of such an approach is often hindered by the sheer complexity of cause-effect relationships and a lack of understanding of the sector specific contributions to effects occurring at a broader ecosystem scale (Smith et al. 2016). While BNs cannot be used to solve the issue of lacking mechanistic understanding between pressures and states, they allow exploring likely risks in the face of uncertainty by testing different mathematical relationships and looking at relative rather absolute changes.

The here presented BN models depict current and planned spatial management measures in the German Bight aimed at integrating Blue Growth and conservation objectives. The models in chapter 5 were extended to include compliance of fishermen to fishing restrictions inside closed areas as well as climate change-induced increases in temperature. This enabled testing the likely risks of the management system in place on ecosystem components and evaluating its performance. Results allow for some careful conclusions on whether spatial management in the German Bight spearheaded by MSP can support environmental targets under conservation objectives of the MSFD or not.

The analysed indicators in this thesis are not specific MSFD indicators per se. Therefore, results do not represent a formal assessment of GES which is carried out by national working groups of responsible agencies and was thus not the aim of thesis. The indicators are however relevant to descriptor 1 (biological diversity) to close current gaps in community level biodiversity indicators while the DI is relevant to descriptor 6 (sea-floor integrity).

As pointed out in the introduction (section 1.3.2), uncertainties of the impact of effort displacement due to area closures on biodiversity and sea-floor integrity is highest in remaining open areas. Results of this thesis suggest that 1) indicator values are overall not likely to worsen beyond closed areas due to effort displacement, and 2) that some increases in indicator state inside OWFs and Natura 2000 are to be expected due to cessation of fishing. However, this only applied to areas where fishermen were assumed to comply with regulations.

Change in indicator state e.g. due to human activities can generally be evaluated based on a trend direction or a target level (Rochet & Trenkel 2003). In terms of changes in trends, BN predictions can be interpreted in two different ways; first, by examining changes in the mean value of the indicator nodes, or by looking at changes in the individual node states.

The mean values of indicators did not change significantly across all indicators and all scenarios, meaning they were still within the confidence interval of the standard deviation. Although managers may be interested in a single value, this is not how a spatial BN prediction should be used. Given that the BN models were populated with spatial data from the entire German Bight, the mean value represents an average of a heterogeneous area which explained the high standard.

As pointed out in chapter 4, observing changes in the likelihood of individual states is a more useful way to evaluate risks and trade-offs in management scenarios. Based on this definition, the DI likely faces a worsening in 1 - 8 % of the area compared to the current state, depending on whether weightings for the different trawl fleets were assumed. Results for the DI and the remaining indicators can only be compared relatively because scenario assumptions and data were different in both chapters. However, the amount of area closures that were assumed was roughly similar. Here, the likelihood increased for cod and S under all scenarios of being in the highest state while the likelihood of being in the lowest state decreased. This was also the case for the CSI with the marked difference of the scenarios that simulated a temperature increase (Chapter 5). Predicted map outputs of the CSI suggested that values could decline in up to 44 % of the study area depending on the assumed temperature increase. This clearly illustrates that conservation success will also depend on factors that are not controllable by management with differing risks and opportunities for the recovery of species and communities potentially overriding management actions. Authors have already suggested that targets of GES may not be met due to climate change (Lynam & Mackinson 2015). Others have suggested that member states may use this fact to rebut legal arguments if GES was not reached due to the "force majeure" nature of climate change being outside of their control (Elliott et al. 2015). The CSI predictions showed significant declines under the climate change scenario. However, BN results also exemplified, that the opposite is conceivable for other indicators which may benefit from warming temperatures. Predicted increases in species richness are for example in accordance with observed long-term trends in richness in the Southern North Sea, which were attributed to climate change (Quante & Colijn 2016).

The assessed indicators are not fully operational. However, testing them against a specific target under the various scenarios allows assessing whether hypothetical management

objectives were met or not. The DI has a specific target stating that if values exceed a value of 1, mortality rates of the benthic community are larger than their recovery potential. The CSI has two threshold values that distinguish communities from being highly resilient (< 0.165) to intermediately sensitive to sensitive (> 0.31) against additional mortality from fishing. For the study area, a reasonable management goal could therefore be to "restore" the community to CSI values of > 0.165 as to ensure a higher proportion of slow-growing, late reproducing and large bodied individuals in the community. For cod and S such targets or thresholds do not exist and are difficult to derive for S without a better mechanistic understanding of the relationship between disturbance, ecosystem processes and S. For cod it could however be a societal goal to re-establish cod as a species that occurs throughout the German Bight (Heessen 1993). Therefore, a hypothetical target could be assumed for abundance distribution of cod to be \geq 1, which equates to cod being present in any given unit area. The trained BN predicted cod to occur in only 60 % of the study area.

BN scenarios showed that these defined targets would not be reached for any of the three indicators under any scenario (Table 1).

Table 1. Summary of indicator properties used in the BN models, the expected trend direction and a potential management target (CSI: Community Sensitivity Index to fishing; DI: Disturbance Indicator; S: Species richness; Cod: abundance distribution of cod) as well as synthesis results showing the percentage of the study area the proposed indicator targets will be likely reached under selected scenarios. OWF = Offshore Wind Farm

	CSI	DI	S	Cod
Level	Community	Community	Community	Species
Thesis chapter	2, 3, 5	4	2, 5	2, 5
Group	Demersal fish	Benthic species	Demersal fish	Demersal fish
Trend direction	increasing	decreasing	increasing	increasing
Target	> 0.165	< 1	-	>= 1
Baseline (% area	41 %	95.9 % (DI _w)	-	59.6 %
>= target)		98.6 % (DI)		
OWF/N2000*				
upper bound	51.6 %	99.3 %	-	75.6 %
lower bound	42.8 %	94.7 %	-	60.7 %
OWF/N2000 & CC**				
upper bound	40 %	-	-	85 %
lower bound	30 %	-	-	71.8 %

*OWF/N2000 refers to Scenario S1 in chapter 5 (construction of OWFs and implementation of Natura 2000 sites till 2020) or the full displacement scenario in chapter 4 (construction of OWFs) **OWF/N2000/CC refers to Scenario S3 in chapter 5 (including a temperature increase of 0.25° C). Upper bound refers to BN predictions for the unweighted DI and the indicator nodes of CSI, S and cod; lower bound refers to the predictions of the weighted Disturbance Indicator (DI_w) and the respective protection nodes of the CSI, S and cod in the BN models.

There is however a considerable difference between indictors. The DI_w i.e. comes very close to meeting its target in the entire survey area (DI_w: 99.3 % and DI: 94.5 %). For the remaining 5 % of the area, values suggest unsustainable levels of benthic disturbance when equal impact of fleets was assumed (DI). Managers would have to decide whether this is still an acceptable level or whether this should trigger a management response. For cod, predictions range from 60.7 % to 85 %, depending on whether increases in temperature and protection effects were included. For the CSI, the predicted range was lowest with only 30 % to 51.6 % of the area to reach the target. However, the initial percentage of area above target value was already quite low in the baseline BN).

3.2 Potentials and caveats in using results for management

As previously pointed out, the precise relationship between biodiversity indicators and fishing effort is often not known and therefore specifying the relationship can only test potential pathways. Relationships between trawling and S, CSI and cod were inferred from the correlative structure in the empirical spatial data sets while in the case of the DI, the relationship was predetermined through the specified formula of this index. Using the correlative structure in the data to train the BN is known as constraint-based structural learning. Given that trend directions are known for many indicators, several mathematical relationships could have also been tested subsequently by specifying them in the indicator node. Based on results from chapter 3 an exponential decline could have been defined for the CSI node. Structural learning is less used in environmental research and it is said that setting causal connections would generally lead to better model predictions (Uusitalo 2007). In fact, sensitivity to findings was considerably higher in BN models in chapter 4, where the DI node was specified as quotient of its two parent nodes (mortality from trawling and resilience). However, a better performance is expected compared to a structurally learned relationship with multiple parent nodes and variability in the data. The DI is an excellent conceptual indicator emphasising the idea of risk analysis by combining vulnerability of ecosystem components and the occurrence likelihood and magnitude of a pressure. However, it is not based on empirical data, and various modelled outputs and ecological assumptions were used to derive the index, which is potentially increasing uncertainty of predictions.

S was most sensitive to trawling in the BN models. Applying the mean value approach presented in chapter 2 helped to address the sensitivity issues often encountered in biodiversity indices and especially in S (Greenstreet & Piet 2008). However, the BN somewhat distorted the relationship between S and otter trawls by assuming a continuous

decline whereas, the highest and lowest values were both found at low trawling effort (leftskewed unimodal distribution). While attention must always be paid in using model predictions in an actual decision making process, the results of the DI and S have to be interpreted more cautiously.

The BN models represent the best available and accessible knowledge. The analysis in chapter 4 was carried out under the auspice of a European project and thus, Vessel Monitoring System (VMS) data and international catch data were available to clearly distiguish fleets down to the metier level. This was not the case for the analysis in chapter 5. Therefore the model could not be strengthenend by access to international logbook data. Also, monitoring data of OWF sites in the German EEZ are not freely accessible. By law, OWF developers are required to pay for monitoring before, during and after construction. However, this has created a grey zone in which ownership and usage rights of the data are not quite clear. Therefore it was unfortunately not possible to undertake an in-depth analysis of German operational OWFs as originally envisioned. Research results from Germany's first OWF test site "Alpha Ventus" were considered (Beiersdorf & Radecke 2014; Hube 2014). However, Alpha Ventus features only 12 turbines and therefore is not representative for other German OWFs comprising usually 80 turbines. Generally, the longest term study on OWF effects on demersal fish fauna in the North Sea reaches back seven years (Stenberg et al. 2015). Given a general time lag of fish communities to disturbance, a complete picture of OWF effects on biodiversity is still lacking. Gaining empirical knowledge of large scale OWF effects at the EEZ scale have not been attempted and research generally focusses on change inside wind farms (Lindeboom et al. 2015). Once more information become available, this can be easily integrated into the models. Specifically, on potential negative effects of OWFs on fish biodiversity and benthic communities which were not considered in this thesis due to a lack in evidence.

The scenarios that were used are based on the latest information on OWF development plans from the Federal Maritime and Hydrographic Agency (BSH) and the latest draft on management plans in Natura 2000 areas. This currently represents the best guess of future developments in the German Bight. The presented BN in chapter 5 could have also been used in tactical decision making to analyse trade-offs and low impact options of prioritising certain uses in specific areas over others, e.g. testing optimal sites for OWF developments. Such an exercise was actually never carried out prior to the implementation of the German MSP (Jay et al. 2012). This issue has now become obsolete, given that OWFs are solely developed in specific clusters which have grid connection, regardless of whether they would be placed more sustainably elsewhere.

Using the BN models the focus was on risks caused by bottom trawling. Therefore, not all economic activities that are carried out in certain areas of the EEZ such as sand and gravel extraction were included. However much like the challenges of integrating multiple objectives from Blue Growth to conservation, this holds also true for models. From a science perspective, models cannot reliably integrate the full suite of different uses due to difficulties in dealing with non-linearity in the system, which again makes it challenging to quantify cause-effect and impact on different ecosystem components. There is a trade-off between predictive power declining and uncertainty increasing with more model components. It is about finding the "sweet spot" between model complexity and uncertainty (Collie et al. 2014). Models provide great insights but will allways be flawed or limited in their view. In the words of Box and Draper (1986) "[...] all models are wrong, but some are useful". BNs certainly qualify as useful tools.

The spatial extend to model effects in the EEZ of the German North Sea was chosen because this is the management boundary for the national maritime spatial plan. Management boundaries do not reflect ecological boundaries of course. Therefore, a potential next step for scenario developments may be to model cross-country case studies for the Southern North Sea to adequately reflect the trans-boundary nature of ecosystem components as well as activities. For example, development plans exist in neighbouring countries that far exceed current development scales of German OWFs, which have been reduced from the initial 25 GW to 15 GW to be reached in 2030 (EEG 2014). The company TenneT has submitted plans with almost double the amount of OWF in the German North Sea EEZ in a single wind farm (7000 turbines) to be built on the Dogger Bank in the Dutch EEZ. If this project was to come to fruition, the cumulative effects of these farms may cause risks for biodiversity that are not as cautiously optimistic as the predictions presented in this thesis.

Analyses in this thesis were based on a risk assessment framework described by Cormier et al. (2013) to conduct spatially explicit and quantitative Environmental Risk Assessments (ERAs), concerned with spatial management questions. There are other established risk assessment frameworks such as Integrated Ecosystem Assessments (IEA; Levin et al. 2009) or the conceptual DPSIR (Driver-Pressure-State-Impact-Response) (Elliott 2002). The latter has been adapted in various ways, e.g. to APSR (Activity-Pressure-State-Response; Greenstreet et al. 2009) or to include human welfare in the latest DAPSIWRM framework (Elliott et al. 2017).

Another risk assessment method that has recently gained a lot of attention in the European policy and science community are bow tie diagrams which can be used to describe and analyse risk events by visualising relevant controls along a pathway from causes to consequences (Ferdous et al. 2013; Mokhtari et al. 2011). The bow tie analysis has also been applied in an EBM context (Cormier 2013; Cormier et al. 2015). What the bow tie adds to the table is the inclusion of barriers representing existing management or mitigation measures that are placed between the causes and the risk, and the risk and consequences. This enables the analysis of the performance of management and mitigation systems in place, in how well they perform in reducing a risk or essentially reducing a pressure, so as to not harm ecosystem components. In a bow tie, management performance is characterised by three elements: management effectiveness, compliance and escalation factors. Effectiveness represents the technical specificities of the measure in reducing a specific pressure. Compliance refers to actors not conforming to set regulations and escalation factors can be any variable that is outside of the management realm but has the ability to impact or undermine management success. The latter could be caused by a drastic change in market forces, climate change, or change of a political system such as the Brexit (Boyes & Elliott 2016). In the frame of this thesis, methods were presented to calculate compliance of fishermen based on VMS pings. The evaluation of management performance in terms of other kinds of compliance or even compliance from different sectors will likely require data and methods from social science. Also, the technical effectiveness of a measure as well as different escalation factors will require potentially new sets of data.

Recently, BNs have been used in combination with bow tie diagrams to overcome their purely descriptive capabilities by adding probabilities and conditional dependencies between components (Badreddine & Amor 2013; Khakzad et al. 2013). Based on this work, a suite of workshops under the ICES Working Group on Marine Spatial Planning and Coastal Zone Management (WG-MSPCZM) was conducted in which a bow tie BN meta-model was developed and applied to two case studies (ICES 2016b). A paper on this method to bridge the science policy interface is about to being submitted (Cormier et al. in prep.).

3.3 The continued challenge to integrate Blue Growth and conservation objectives

Challenges in succeeding to implement EB-MSM are manifold. Contributing factors may be that change in such a complex governance environment down from EU to sub-national levels is simply slow. Given that there are more than 200 legal instruments dealing with the (sustainable) use and/or conservation of marine environment (Beunen et al. 2009), it surely is

not due to a lack thereof. The current policy landscape has set the stage at least in theory for integrative management that balances economic uses with conservation and has reaffirmed sustainable development and conservation of biodiversity in its multiple strategies. But no change comes easy. It took for example fifteen years to finally designate Natura 2000 sites. The traditional divide between conservation legislation which has developed separately from economic sector focussed legislation is still palpable and various authors have attested the marine EU policy landscape to be highly fragmented with different ideas of what reaching sustainability entails. This included contradicting, unclear or partly overlapping competencies between legislations (Jones et al. 2016; Qiu & Jones 2013; Rice 2011; Salomon & Dross 2013).

It seems however that some of the more imminent issues lie at the member state and management level. For example, the implementation of the MSFD requirements is anything but ambitions. The vast majority of indicators under D1 and D6 of the German monitoring programme are not operationalised, with the exception of marine and coastal birds and marine mammals, and no novel indicators were proposed to address gaps. A recent comparison of the degree of implementation of D1 indicators ranked Germany amongst the best scoring countries along with France, Greece and Spain (Hummel et al. 2015). The German Programme of Measures (PoM) is also vastly relying on existing measures preserving the status quo. Measures to conserve biodiversity are again targeted at species level and are just adding to the established legal framework without being inventive. A review of the PoMs from Greece, the UK and Spain showed clear differences from not having submitted a PoM in the case of Greece, to minimum requirements in the UK, to more comprehensive measures in Spain (Boyes et al. 2016). The MSFD tried to keep financial and administrative burden low by requiring building on existing measures. This may have hampered a real attempt to achieve GES in many countries (Boyes et al. 2016).

The current picture of the MSP process in Germany is not much brighter. The theoretical MSP framework described in chapter 1 is an idealised depiction that is not rooted in reality (Jay et al. 2016). Until now, MSP in Germany is characterised through an ad hoc planning with a clear emphasis on OWF developments and Blue Growth in general rather than incorporating adaptive science to achieve sustainable development. Reviews of international and European MSP case studies show that MSP is currently not living up to its standards (Collie et al. 2013; Jones et al. 2016). Jones et al. (2016) go as far as saying that MSP should be renamed into "strategic sectoral planning" and that "*Blue Growth priorities are diverging*

from and potentially competing with ecosystem-based MSP". They further point to the growing tension between the MSFD and the MSPD.

There are many interrelations and opportunities for MSP and MSFD to cross fertilise beyond biodiversity. These pertain in particular to invasive species (D2), changes in hydrography (D7) and energy and underwater noise (D10), for which OWFs and shipping are main drivers. Maccarone et al. (2015) made a case for integration of both instruments to achieve goals under D10. For now, actual linkages between MSFD and MSP remain just that, an opportunity. If in 2020 GES should officially not be reached it may be an incentive for responsible agencies to better integrate their work and help the understanding that MSP can offer benefits towards MSFD goals while MSP will not meet its guidelines (chapter 1) if it does not integrate conservation more effectively in the future.

Whether the European Commission will facilitate the integration remains to be seen. Shipping is the largest and OWF development the most promising economic activity in Germany and several other European countries (Emeis et al, 2015). Both sectors do not rely on healthy and diverse oceans. There is a clear prioritisation of economy over environment, which is endorsed by the large EU maritime nations (e.g. UK), where MSP was termed the far more practical concept than the MSFD to implement sustainable development (Brennan et al. 2014). In order to achieve a real balance between Blue Growth and conservation, political will needs to evaluate its priorities and value systems.

3.4 Outlook on operationalising EB-MSM: Science versus value-based decision making

In the European research community a lot of research attention went into quantifying pressure-state relationships between ecological indicators and fishing pressure to clearly suss out the direct and indirect effects of trawling on demersal habitats, fish and benthic communities. While some important knowledge was gained, relationships were never clear cut and no final suite of indicators emerged that could fulfil all selection criteria while providing robust targets and thresholds. Reasons for this are largely identical to the ones discussed in this thesis. The sheer complexities of how pressures act on ecosystem components and the variability down to different impacts of fishing gear can lead to many potential pressure-state change trajectories that increase in complexity, when multiple pressures are attempted to be integrated (Smith et al. 2016). The potentially synergistic or antagonistic effects of cumulative pressures are still largely unknown. The choice of the European Commission to put pressure-state relationships at the heart of the MSFD was ill-

advised in hindsight given that most indicators are, in contrary to expectations, not operational.

This surely does not mean that science-informed decision making is not possible in meeting current policy objectives. Despite the bottlenecks in operationalisation of indicators this thesis provides evidence that community-level biodiversity indicators are useful as surveillance indicators. Distribution maps of biodiversity indicators as presented in this thesis could serve as source for precautionary adaptive management. Further, scope exists to operationalise indicators by using trait-based information that establish an ecologically link between state and fishing pressure, as it was the case with the developed CSI. However, as pointed out earlier, dedicated empirical research is needed to test hypotheses of biodiversity and ecosystem functioning. The risk analyses that were carried out in this thesis provided some very useful insights into potential risks of direct and indirect effects of planned spatial management measures on fish biodiversity and the vulnerability of benthic species. BNs allow exploring likely risks in the face of uncertainty by testing different mathematical relationships and looking at relative rather absolute changes. Their probabilistic nature makes the inherent uncertainty in the system transparent to decision makers by providing a range of future outcomes instead of a single prediction with large confidence intervals. The flexibility of BNs further allowed constructing models that closely mirror current components of the management system in the German Bight. The methodology used could thus facilitate the pending review of the German MSP.

No matter how much we learn about our impact on the environment, there will always be uncertainties in scientific assessments. The question is how policy makers and managers will deal with these. In some instances the only sensible option would be to truly embrace the precautionary principle. Pikitch et al. (2004) proposed, that in data-rich environments EBM evolves toward a system in which performance indicators for each ecosystem-based objective are monitored with fewer precautionary measures. Naeem et al. (2012) proposed to "go beyond the precautionary principle of conserving biodiversity to a predictive science that informs practical and specific solutions to mitigate and adapt to its loss". The North Sea is classified as data-rich by all means. However, as this thesis exemplifies data needs to uncover effect sizes in such a chronically disturbed system, available data sets are likely beyond what can be achieved. Therefore, transcending the precautionary approach seems like an unrealistic idea. In fact, this principle should be invoked much more frequently in instances of insufficient empirical evidence to "err on the side of caution". The issue of science-based versus value-based decision making is exemplified by current delays with the implementation of management plans and fleet-specific fishing restrictions in Natura 2000 sites. A proposal was made to exempt traditional shrimp trawler below 221 kW from restrictions in certain areas. One reason for this was because their impact on the seabed system was judged to be less invasive than fleets fishing with heavier gears. This is now contested by other stakeholders, who would also like to be exempted (pers. comm., Torsten Schulze, TI). In the absence of clear scientific evidence on gear-specific impacts on marine habitats it is up to decision makers to invoke the precautionary principle. In other words, these decisions essentially become normative in the sense that it is a societal question of "how much risk one is willing to take in order to facilitate Blue Growth while potentially harming the environment", or "how much does the society actually want to conserve?" Therefore, these questions refer to the value that the society attributes to protected environments. Generally, the prioritisation between Blue Growth and conservation needs to be discussed at the societal and not the scientific level. Policy makers should incorporate public opinion in their setting of management targets.

4. Conclusion

The operationalisation of EB-MSM to integrate Blue Growth with conservation objectives will challenge managers and scientists alike for years to come. The implementation of this approach remains an institutional challenge and will largely depend on political will and capacity of involved agencies. What science should focus on is to facilitate informed decision making and provide guidance on cross-cutting themes that are relevant to decision makers from different policy backgrounds to bridge the divide between Blue Growth and conservation legislation.

Despite the wealth in data and existing knowledge, gaps remain to fully understand the functional relationship between fishing effects on community biodiversity. Therefore, to facilitate the EB-MSM approach from a scientific standpoint will require well designed empirical research and further scientific exploration of hypotheses underlying biodiversity. Whether specific pressure-state relationships with clearly defined and robust management targets will be attainable for biodiversity indicators in the near future remains to be seen. In the face of uncertainty, risk analyses are paramount and in combination with spatial BN models proofed to be a very useful tool to evaluate risk under different scenarios while integrating multiple users and ecosystem components.

We are still changing the marine environment at a quicker pace than the understanding that we have to achieve sustainable management of resources. In the face of uncertainty, the integration of Blue Growth with conservation objectives will require a concerted effort from diverse stakeholder. Policy makers and managers need to prioritise both elements at least equally and embrace the precautionary principle instead of hoping for specific management targets; the latter will have to actively engage in cross-policy and cross-agency collaboration while scientists have to bridge the science-policy interface by adapting models to reflect practical management-relevant issues. Finally, society needs to decide upon the kind of sustainability that it wants for the future.

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Acronyms

BD	Birds Directive
BN or BBN	Bayesian Belief Network
BSH	Federal Maritime and Hydrographic Agency (BSH)
CART	Classification and regression trees
CBD	Convention of Biological Diversity
CFP	Common Fisheries Policy
CSI	Community Sensitivity Index to fishing
СТР	Conditional Probability Table
DAG	Directed Acyclic Graph
DCF	Data Collection Framework
EBM	Ecosystem Based Management
EB-MSM	Ecosystem Based Marine Spatial Management
EC	European Commission
EEZ	Exclusive Economic Zone
EIA	Environmental Impact Assessment
ERA	Environmental risk assessment
EU	European Union
GAM	Generalised Additive Model
GASEEZ	German Autumn Survey of the Exclusive Economic Zone
GES	Good Environmental Status
GIS	Geographical Information System
GSBTS	German Small-Scale Bottom Trawl Survey
HD	Habitats Directive
IBTS	International Bottom Trawl Survey
ICES	International Council for the Exploration of the Sea
JRC	Joint Research Centre of the European Union
MSP	Marine or Maritime Spatial Plan(ing)
MSFD	Marine Strategy Framework Directive
N_1	Hill's N ₁ (taxonomic biodiversity indicator)
OSPAR	Oslo Paris Commission
OWF	Offshore Wind Farm
PoM	MSFD Programme of Measures
S	Species richness
SEA	Strategic Environmental Assessment
SMA	Spatially Managed Area
VMS	Vessel Monitoring System
WFD	Water Framework Directive

Glossary

Blue Growth	EU long term strategy to support sustainable growth of maritime economies and the sustainable development of marine areas	
Bayesian Belief Network (BN)	Probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph	
Community-level indicator	Measure of processes between species in contrast to species- or ecosystem level indicator	
Cumulative effects	Combined impact of multiple pressures over space and time which can be additive, antagonistic, synergistic	
Ecological indicator	Measure to communicate information about ecosystems and the imp human activities have on them to groups such as the public or government policy makers	
Ecosystem Based Management	Considers the whole ecosystem, including humans featuring the cumulative pressures they are exerting	
Ecosystem	Elements of the natural environment (communities, habitats, resources)	
component Environmental Risk Assessment	Frameworks with quantitative or probabilistic measures of risk to evaluate spatial management scenarios comprising Risk identification, Risk analysis and Risk evaluation	
Functional diversity indicator	Measure of the number of functionally disparate species within a population (e.g. different life-history traits)	
Good Environmental Status (GES)	Main goal of the MSFD to promote an environmental status of marine waters where these provide ecologically diverse and dynamic oceans	
Marine Strategy Framework Directive	Strategy to achieve or maintain GES of marine ecosystems which shall apply an EBM, ensuring that the collective pressure of human activities is kept within levels compatible with the achievement of GES by 2020	
Maritime Spatial Planning	Cross-cutting policy tool that contributes to Blue Growth while applying an EBM	
Natura 2000	(Marine) reserves devised under the Habitats and Birds Directive	
Operational indicator	Measure that has well-understood relationships between state and specified anthropogenic pressure(s) & a defined targets	
Pressure-state relationship	Relationships between the state of an ecosystem component and a specified anthropogenic pressure, both measured through indicators	

Species diversity	Species diversity is the number of different species that are represented in a given community and consists of two components: species richness and species evenness
Surveillance Indicators	Indicators where links to anthropogenic pressures are either weak or not sufficiently well known & with insufficient evidence to define targets and support formal state assessment
Taxonomic biodiversity indicators	Indicator that measures species diversity or richness

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Declaration on oath

I hereby declare, on oath, that I have written the present dissertation by my own and have not used other than the acknowledged resources and aids.

Hiermit erkläre ich an Eides statt, dass ich die vorliegende Dissertationsschrift selbst verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

Hamburg, 27. April 2017

Signature

Appendix I: Allgemeine Zusammenfassung

In der südlichen Nordsee, einer der am intensivsten genutzten marinen Gebiete der Erde, werden verstärkt räumliche Managementmaßnahmen mariner Räume implementiert. Verschiedenste Akteure konkurrieren hier um marine Flächen und üben einen chronischen Druck auf das Ökosystem aus. Die dominierenden Konflikte bestehen zwischen dem Ausbau von Offshore-Windparks (OWP), dem Fischereisektor und dem Umweltschutz. Die Folgen von räumlichen Gebietsschließungen wie dem Bau von OWPs oder der Einrichtung von Natura 2000 Schutzzonen, sowie der daraus folgenden Verdrängung der Fischerei in andere Gebiete sind kaum abzuschätzen.

Die politische Landschaft, welche das Management europäischer Gewässer reguliert, ist ähnlich komplex. Eine der zukünftigen Herausforderungen stellt das Ausbalancieren von ökonomischem Wachstum ("Blue Growth") mit der Gesundheit des Ökosystems, insbesondere der Biodiversität, dar. Die Meeresstrategie-Rahmenrichtlinie (MSRL), eine der Schlüsselstrategien, die die Mitglieder der Europäischen Union (EU) national umsetzen müssen, verlangt die Erreichung eines guten Umweltzustandes bis 2020 (GES "good environmental status"). Darüber hinaus müssen EU-Mitgliedsstaaten unter der Maritimen Raumordnungsdirektive (MSPD "Maritime Spatial Planning Directive") maritime Raumpläne (MSP "maritime spatial plans") einrichten, um eine nachhaltige Nutzung der marinen Ressourcen zu erreichen. Beide Instrumente (MSP und MSRL) zielen darauf ab, einen ökosystembasierten Managementansatz umzusetzen. Defizite in der Implementierung bestehen u.a. darin, dass es keine räumlich expliziten Indikatoren und dazugehörige Schwellenwerte gibt, die das Erreichen multipler Zielvorstellungen messen können. Außerdem fehlen gesamtheitliche Bewertungssysteme, die es ermöglichen Risiken, Optionen und Unsicherheiten des räumlichen Managements gegeneinander abzuwägen.

Das Ziel dieser Dissertation ist es, die Lücke zu schließen, indem räumlich explizite Indikatoren im Rahmen von Belastungs-Zustandsbeziehungen zwischen Fischerei und dem Ökosystem operationalisiert werden, um im zweiten Schritt Risiken, Optionen und Unsicherheiten mittels wahrscheinlichkeitsbasierter Modelle ("Bayesschen-Netzen") im Bereich der räumlichen Planung zu bewerten. Die Analyse wird in der Deutschen Bucht, insbesondere der Ausschließlichen Wirtschaftszone (AWZ) der Nordsee, durchgeführt und fokussiert sich auf benthische Gemeinschaften, v.a. auf die demersale Fischfauna.
Kapitel 1 dieser These gibt einen Einblick in relevante europäische und deutsche Gesetzgebungen und räumliche Managementansätze. Das schließt eine Analyse von möglichen operativen Zielsetzungen zwischen "Blue Growth" und der momentanen Gesetzgebung im Umweltschutz ein. In Ermangelung spezifischer Managementziele, wurde der Schutz mariner Biodiversität als roter Faden der Arbeit ausgewählt.

Ökosystembasiertes räumliches Management benötigt speziell zugeschnittene und räumlich Indikatoren. Die Kartierung Biodiversitätsindikatoren explizite von die Gemeinschaftsprozesse abbilden ist nicht leicht. Aus diesem Grund befasst sich Kapitel 2 mit dem Vergleich zweier Methoden zur Kartierung von Biodiversitätsgemeinschaftsindikatoren. Weiterhin wird eine einfache Methode für den Umgang mit extrem seltenen Arten vorgestellt, die normalerweise nur sehr schwer modelliert werden können. Schließlich wird ein neuer merkmals-basierter Indikator, der "Community Sensitivity Index to fishing" (CSI), entwickelt: Merkmale wie Wachstum, maximale Länge, sowie der Eintritt in die Geschlechtsreife gehen darüber Auskunft, wie sich Fischereidruck auf die Verwundbarkeit bestimmter Fischgemeinschaften auswirkt. Als Vergleichsindizes wurden die etablierten taxonomischen Indizes Artenvielfalt und Hill's N1 genutzt. Der Hill's N1 kombiniert sowohl Vielfalt als auch Abundanz. Während sich beide Kartierungsansätze als abhängig vom Kontext verstehen, ermöglicht der sogenannte indirekte Ansatz eine übergreifende Einschätzung von Fisch-Biodiversität und Sensitivität im europäischen Kontext. Die Ergebnisse zeigen des Weiteren, dass "Biodiversitäts-Hot-Spots" unter zukünftigen Natura 2000 Schutzzonen nicht besonders gut geschützt werden würden.

Zusammenhänge zwischen Fischereidruck, Umwelteinflüssen und Biodiversität zu quantifizieren, um Belastungs-Zustandsbeziehungen zu bewerten, ist bis jetzt nur in wenigen Fällen gelungen. In **Kapitel 3** werden diese Zusammenhänge mit Hilfe des CSI getestet. Dabei werden räumliche Modelle unter Verwendung von Daten der internationalen Grundschleppnetz-Flotte untersucht, um zu testen, ob der CSI als Beratungshilfe für Meeresmanagement angewendet werden könnte. Zunächst wurde dazu der Fischereiaufwand mit Hilfe von Daten des Schiffsüberwachungssystems (VMS) auf Fangflottenbasis interpoliert. Eine Reihe von regressionsbasierten Techniken hat in Bereichen, in denen die küstennahe Baumkurrenflotte hohen Druck ausübt, einen signifikanten Rückgang von Indexwerten aufgezeigt. Der CSI könnte also für diese Flotte angewendet werden. Die Aussagen des Indizes waren in anderen Gegenden weniger eindeutig oder haben sich im Gegenteil sogar gewendet, weil hier der Einfluss von Umwelteinflüssen, v.a. Tiefe, stärker war. Die Ergebnisse zeigen, dass es weiterhin schwierig bleibt, die Auswirkungen von

Fischereidruck in einem chronisch gestörten System zufriedenstellend in absoluten Zahlen darzustellen. Daraus folgt, dass sich künftige Evaluierungen eher auf risiko-basierte und relative statt absolute Auswirkungen konzentrieren sollten.

Kapitel 4 bietet eine übergreifende Einführung in quantitative Standards der Risikoabschätzung. Eine Meta-Analyse der aktuellen Anwendung von Risikobewertungen in der Raumplanung hat dabei gezeigt, dass sich die Forschung in der Anwendung des Konzepts nicht einig ist. Das standardisierte Risikokonzept wurde schließlich dafür genutzt, um das Risiko der Verlagerung von Fischereidruck durch den Bau von OWP räumlich abzuschätzen. Hier wurde speziell auf die Verwundbarkeit der benthischen Fischgemeinschaft geschaut. Die Auswirkungen wurden dabei durch einen Störungsindex ("Disturbance Index", DI) erklärt, der durch den Quotient von Fischereimortalität und Resilienzpotential derselben berechnet wird. Das Verfahren wurde mit Hilfe der Kopplung von Bayesschen Netzen (BN) und einem geographischen Informationssystem angewendet (GIS). Dabei wurden sukzessiv Wahrscheinlichkeitsverteilungen für betroffene Fischereiflotten im Modell verändert, um antizipierte Veränderungen zu reflektieren. Die Ergebnisse zeigen, dass benthische Gemeinschaften wahrscheinlich einem 8% höheren Risiko der Verschlechterung ihrer DI-Werte ausgesetzt sind. Im Kontext der MSRL würde das bedeuten, dass der GES nicht erreicht werden würde.

Schließlich wurde in Kapitel 5 ein ähnlicher Ansatz gewählt, um die Auswirkungen einer Reihe von geplanten Managementmaßnahmen mariner Räume auf die Biodiversität der Fische zu erforschen. Diese sind OWPs, die Natura 2000 Reservate sowie die Schollenbox. Es Ursache-Wirkung-Zusammenhänge wurden speziell zwischen Fischfang mit Grundschleppnetzen und Umwelteinflüssen auf den CSI, die Artenvielfalt und die räumliche Abundanz von Kabeljau - einer Art, die in Deutschland als gefährdet eingeschätzt wird analysiert. In Kontrast zum vorigen Kapitel wurden die BN-Modelle mit empirisch abgeleiteten Entscheidungsregeln für eine räumliche Verschiebung von Fischereidruck aufgesetzt. Des Weiteren wurde das Einhalten von Vorgaben durch Fischer, Schutzeffekte innerhalb und außerhalb der für die Fischerei geschlossenen Gebiete und verschiedene Bebauungsstadien von Windparks berücksichtigt. Zusätzlich wurden Temperaturerhöhungen, die durch den Klimawandel entstehen, simuliert. Dabei wurden insgesamt zehn kurzfristige (fünf Jahre) und mittelfristige (15 Jahre) Szenarios analysiert. Zudem wurde getestet, wie stark der räumliche Fischereiaufwand der kleinen Baumkurrenfischerei bis zum Jahr 2020 gesenkt werden müsste, um Grenzwerte des CSI einzuhalten und letztendlich den GES zu erreichen. Die Szenarios haben ergeben, dass der räumliche Aufwand um 9% pro Rasterzelle reduziert werden müsste. Es wurde ebenfalls gezeigt, dass Schutzeffekte, die durch ganzer Schließung Bereiche entstanden sind, negative Auswirkungen durch Fischereiumverteilung abpuffern. Lokal kam es jedoch zu Verschlechterungen der Indikatoren durch Nichteinhaltung der Regularien durch Fischer. AWZ-weite Effekte wurden allein durch die simulierte Temperaturveränderung erreicht, die zu einer erhöhten Artenvielfalt und erhöhten Abundanz von Kabeljau führten. Der CSI nahm allerdings in 44% des Gebietes ab. Der Erfolg von Meeresschutz wird also auch auf Faktoren beruhen, die nicht durch Managementmaßnahmen kontrollierbar sind. Dabei gibt es verschiedene Auswirkungen, die sowohl zur Erholung, als auch zur Verschlechterung der Biodiversität führen könnten.

In Kapitel 6 werden die Ergebnisse der Forschungsarbeit zusammengefasst und verbleibender Forschungsbedarf diskutiert. In der Summe bietet diese Arbeit eine übergreifende Analyse des Systems der Raumnutzung in der Nordsee und seiner möglichen Auswirkungen im Bereich der Fisch-Biodiversität. Räumlich angewandte BNs, die Managementszenarien simulieren, bieten ein nützliches Werkzeug für die Betrachtung von möglichen zukünftigen Risiken, Optionen und Unsicherheiten. Die hier erhaltenen Ergebnisse variierten in unterschiedlichen Deutschen Bucht zeigen die Limitationen Habitaten der und von generellen Forschungsaussagen. Neben den bestehenden Schwierigkeiten bei der Operationalisierung von Biodiversitätsindikatoren hat die Analyse die Bedeutung des Verständnisses und der Dynamik sowie die Einflussfaktoren von Ursache-Wirkungs-Prinzipen verdeutlicht. Dieser Bereich benötigt weitere empirische Forschungsarbeiten, die die Lücken im mechanischen Verständnis von einzelnen und kumulativen Effekten von Fischerei und OWPs auf marine Biodiversität untersuchen. Während die Analyse gezeigt hat, dass Umverteilungen von Fischereiflotten keine erhebliche Auswirkung auf die Biodiversität haben, müssen in Zukunft auch die Fischereiaktivitäten benachbarter Länder in die Untersuchungen miteinbezogen werden. Solche grenzüberschreitenden Analysen werden nicht nur für die MSRL und die MSPD benötigt, sie sind ebenso wichtig bei der Adressierung von kombinierten Effekten von Meeresraumplanung in der Nordsee sowie der grenzüberschreitenden Natur von Populationen und Habitaten. Wir verändern das marine Ökosystem nach wie vor schneller, als dass wir es verstehen. Somit ist es schwierig Vorgaben für ein nachhaltiges Management der Ressourcen zu erschaffen. In Kombination mit unklaren Vorhersagen von Effekten des Klimawandels, sollten Meeresraumplaner sich an das Vorsorgeprinzip halten, anstatt auf spezifische Managementziele zu hoffen. MSP in Deutschland ist derzeit durch eine eindeutige Priorisierung von ökonomischem Wachstum gekennzeichnet.

Eine Balance kann nur erreicht werden, wenn Entscheidungsträger den Umweltschutz und Blaues Wachstum zu gleichen Teilen priorisieren. Wissenschaftler müssen sich in Zukunft stärker für eine wissenschaftsbasierte Entscheidungsfindung einsetzen. Es ist an ihnen Modelle und Theorien besser an für das Meeresmanagement relevante Fragen anzupassen. Schließlich müssen wir als Gesellschaft entscheiden, wie Nachhaltig wir unsere Zukunft gestalten wollen.

Appendix II: List of publications

The following four publications constitute the Material and Method section of this dissertation. The list further clarifies the authors' contribution to each manuscript and the current status in the submission process to a peer-reviewed journal.

Chapter 2

Mapping fish community biodiversity as a tool for European marine policy requirements

Henrike Rambo (HR), Vanessa Stelzenmüller (VS), Simon P.R. Greenstreet (SPRG) and Christian Möllmann (CM)

HR perceived the concept of the paper and performed all analyses, VS, CM and SPRG provided valuable advice on the structure and the draft of the manuscript. SPRG further developed the concept of the mean value approach.

Chapter 2 is in press at the ICES Journal of Marine Science.

Chapter 3

Disentangling fishing from habitat effects to explain spatial patterns in fish community sensitivity to fisheries

Henrike Rambo, Vanessa Stelzenmüller, Rabea Diekmann (RD), Christian Möllmann and Marcos Llope (ML)

HR perceived the concept of the paper, performed all graphical presentations, modelling and most text writing in close cooperation with VS, CM and RD. All co-authors provided methodological advice and critically reviewed the manuscript. RD further provided VMS distribution data.

Chapter 3 will be submitted to Marine Ecology Progress Series.

Chapter 4

Quantitative environmental risk assessments in the context of marine spatial management: current approaches and some perspectives

Vanessa Stelzenmüller, Heino O. Fock (HOF), Antje Gimpel (AG), Henrike Rambo, Rabea Diekmann, Wolfgang N. Probst (WNP), Ulrich Callies (UC), Frank Bockelmann (FB), Herman Neumann (HN) and Ingrid Kröncke (IK)

VS performed the risk assessment and text writing under close cooperation with HOF, HR, AG, RD, WNP, UC, FB, HN and IK. HR, AG, RD and WNP performed the literature review. HR further translated the results of the review graphically. Chapter 4 is published in the *ICES Journal of Marine Science* (2015),

doi:10.1093/icesjms/fsu206.

Chapter 5

Exploring the effects of spatial planning and climate change on marine fish biodiversity with the help of spatially explicit Bayesian Belief Networks

Henrike Rambo, Vanessa Stelzenmüller, Christian Möllmann, Rabea Diekmann and Roland Cormier (RC)

The analysis was carried out by HR under supervision of VS. RD provided the VMS distribution maps, RC provided input into the design of the BN model. VM and CM provided feedback on the draft and the structure of the manuscript. RC provided the idea of including management compliance as essential part of the BN models.

Chapter 5 will be submitted to the Journal of Environmental Management.