Linking environmental monitoring data and the predicted effects of climate change for urban coastal management: A case study of Dublin Bay

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A R T I C L E   I N F O

A B S T R A C T

Environmental managers of coastal regions must consider the combined effects of climate change and multiple other stressors simultaneously. While routine monitoring programmes exist, this information is usually summarised as a metric or index for ecological status classification and does not integrate the biological and environmental data in a format that is useful for managers. We present a framework using conditional inference tree analyses and Bayesian Network methodology that synthesises monitoring data, identifies links between environmental and biological variables, and predicts the effects of climate change for Dublin Bay, Ireland. The ecological quality status of phytoplankton biomass was usually high but degraded when silica became limiting. Sediment organic content was positively related to benthic invertebrate richness and the abundance of wading birds, although invertebrate communities were most indicative of pristine conditions when sediment organic content was low. Importantly, climate change simulations showed that the ecological status of Dublin Bay will decline in future, which highlights the importance of removing other stressors from the ecosystem.

1. Introduction

Coastal ecosystems experience increasing anthropogenic pressures, which affect their biodiversity and associated rates of ecosystem functioning (He and Silliman, 2019; O'Hara et al., 2021). Resource exploitation, marine pollution including eutrophication and harmful chemicals, or physical modifications are among the human-driven processes that impact marine ecosystems, particularly in urban areas (Todd et al., 2019). Consequences include resource reduction, habitat modifications or loss, altered hydrodynamics, or altered species interactions, which may lead to loss of foundation species, changes in biodiversity, and productivity (Todd et al., 2019). Simultaneously, climate change undermines marine biodiversity and ecosystem functioning through warming, acidifying and deoxygenating seawater, causing sea level rise and more frequent weather extremes (Hewitt et al., 2016). Representative Concentration Pathways (RCPs) of increasing greenhouse gas concentrations have been developed to model future climate scenarios and estimate potential ecosystem trajectories, including RCP 4.5 and 8.5 illustrating moderate and extreme climate change, respectively (van Vuuren et al., 2011; IPCC, 2013). Despite the importance of biodiversity conservation, climate change mitigation and adaptation has been

recognised with increasing urgency, effective action and societal transformation emerge slowly (Matthews and Wynes, 2022). This may partly be due to the complexity of the problems to solve, the uncertainty about how to tackle the combined effects of multiple stressors, and the uncertainty of whether management interventions will achieve desired outcomes (Côté et al., 2016; Moore and Schindler, 2022).

Various monitoring programmes try to capture environmental and ecological trends and regularly report their descriptive findings as summary metrics or indices. For example, the EU Water Framework Directive (WFD) is a statutory law that defines common principles for monitoring and taking action to achieve or maintain 'good ecological status' in European water bodies (European Commission, 2000). Extensive monitoring activities are routinely reported, however, when information is condensed into proxies for levels of ecological status, it can no longer be used to identify relationships with typical environmental conditions (Voulvoulis et al., 2017; Feld et al., 2020). There are few robust frameworks that integrate the biological and environmental data to characterise and help manage coastal ecosystems for a range of outcomes (Feld et al., 2016). Management of aquatic environments requires an understanding of the links between environmental conditions and biological communities, including predictions of how changing

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climatic conditions may affect these communities (Philippart et al., 2011).

Bayesian Networks (BNs) are a modelling approach that integrates complex systems to enhance our understanding, predict the effects of change, and support decision-making (Kelly et al., 2013). BNs are useful for linking potential drivers, pressures and impacts of multiple stressors in complex ecosystems, presenting probabilistic outcomes of desired biodiversity aspects or ecosystem services following specific management choices or climate change scenarios (Uusitalo, 2007). These models are illustrated as an acyclic conceptual influence diagram that contains nodes (variables) and links (relationships) between them in a directed cause-effect structure, which is easy to interpret and modify by users and stakeholders. Nodes consist of multiple states, i.e. categorical conditions or data ranges, and the links between the nodes represent conditional, probabilistic (Bayesian) relationships (Kelly et al., 2013). BNs apply conditional inference and calculate the overall probabilities that certain variable conditions will be attained. BNs can be used prognostically (given the inputs, what are the outcomes?), or diagnostically (given an output, what were the inputs?). No concept of time or circular connections, such as ecological feedback loops, can be included, which restricts BNs to static, conditional snapshots of a study system. The probabilistic BN outputs include explicit information about the uncertainty of data or predictions in a study system, which also identifies knowledge gaps (Chen and Pollino, 2012).

Dublin Bay is a temperate estuary bordering on a metropolitan area, which is subjected to many common anthropogenic stressors (Fig. 1). Thus, it is a highly suitable case study to test new methods for better management of complex coastal ecosystems. In addition to industrial pressures, agricultural residue and nutrient discharges from rivers and wastewater treatment plants, port activities and their associate risk of pulses of pollution, Dublin Bay is also extensively used for many recreational activities (Brooks et al., 2016; Cabana et al., 2020). All these pressures, in addition to climate change, could affect the system by changing abiotic conditions (e.g. water temperature, salinity, nutrient concentration, or pollutant levels), which in turn may affect biodiversity (e.g. migrating bird population) and ecosystem functioning (e.g. biochemical oxygen demands, nutrient cycling or productivity rates). Dublin Bay is currently protected under several environmental regulations including EU Special Protection Areas (SPAs) and Special Areas of Conservation (SACs) and, unusually for a metropolitan area, is a UNESCO Biosphere (Dublin Bay Biosphere Partnership, 2017). These designations are because of the presence of several rare and internationally important wildlife species and the high ecological value of the habitat. For example, SPA and SAC conservation objectives include maintaining a stable, or increasing, area of 'mudflats and sandflats not covered by seawater at low tide', and protection of populations of several migratory and resident birds including brent geese, redshank, curlew and bar-tailed godwit (NPWS, 2013a, 2013b, 2015a, 2015b). This highlights the importance of effective conservation management and pressure mitigation to maintain or restore favourable conservation conditions.

Here, we present a framework to synthesise environmental monitoring data from Dublin Bay, using conditional inference tree analyses and the Bayesian Network (BN) methodology, to support local managements' decision making by deepening the understanding of the complex linkages between environmental conditions and the diversity and functioning of Dublin Bay. Additionally, key physico-chemical variables, and their possible effects on biological variables, were extrapolated based on climate change projections to provide ecosystem trajectories under different climate change scenarios (IPCC, 2013). Nutrient conditions, sediment organic content and climate change scenarios were linked with intermediate physico-chemical variables to model their effects on phytoplankton, benthic invertebrates and waders, which were selected as socio-economically relevant biodiversity indicators following initial assessment of available data.

Our data analysis was based on the following hypotheses:
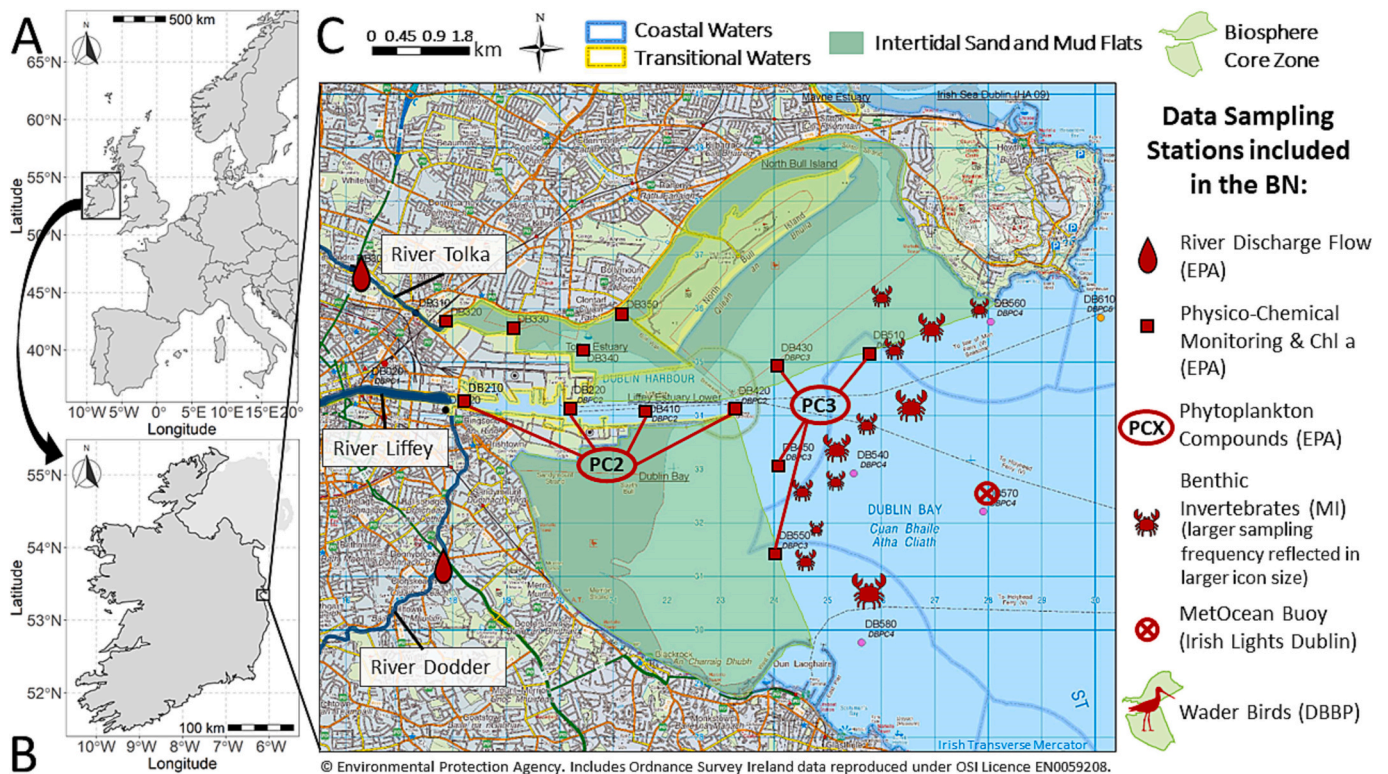

Fig. 1. A, B Dublin Bay in Ireland, C sampling stations from which monitoring data was provided for the BN. EPA: Environmental Protection Agency Ireland; MI: Marine Institute Ireland: DBBP: Dublin Bay Bird Project.

1. Weather and discharges into Dublin Bay affect physico-chemical variables (e.g. nutrient concentrations may increase with sewage discharge, water temperature increases with warmer weather, salinity decreases with precipitation and high river discharge loads, water agitation increases in windy conditions).
2. Physico-chemical variables affect phytoplankton and benthic invertebrates (e.g. phytoplankton biomass increases with temperature; Platt et al., 1987).
3. Phytoplankton growth increases pH and the concentration of dissolved oxygen through photosynthesis (Provoost et al., 2010; Jakobsen et al., 2015).
4. High dissolved oxygen concentrations, pH, and sediment organic content are beneficial to benthic invertebrates.
5. The availability of benthic invertebrates and of habitat area positively affect the abundance of waders.
6. Climate change will affect biodiversity through changes in physico-chemical variables (e.g. warming will increase phytoplankton abundance, but loss of intertidal areas will reduce wader abundance).

2. Materials and methods

To characterise Dublin Bay, a BN was built from available monitoring data following an established iterative process (Chen and Pollino, 2012; Marcot et al., 2006), which included: (i) conceptualising Dublin Bay as a study system; (ii) defining the model structure by selecting variables and specifying links between them; (iii) discretising continuous variables into categorical states; and (iv) populating conditional probability tables. The geographical area covered by the BN includes transitional waters of the River Tolka, North Bull Island and Liffey Estuary and the coastal waters of Dublin Bay (EPA, 2022; Fig. 1).

Dublin Bay was conceptualised holistically by applying the DPSIR framework (Drivers – Pressures – State Change – Impact – Response [Atkins et al., 2011]). We identified natural (e.g. tidal water exchange with the Irish Sea) and anthropogenic drivers (e.g. climate change, urbanisation, agriculture in the hinterland) that exerted pressures on the bay (e.g. input of organic particulate matter, or warming), which changed the state of abiotic environmental variables (e.g. sediment organic content, or water temperature) and thereby had the potential to affect various ecological processes and related biodiversity indicators (e.g. phytoplankton biomass, wader abundance).

The model structure, i.e. the variables represented as nodes in the network and the conditional links among them, was drawn from previous studies (e.g. Brooks et al., 2016; Cabana et al., 2020; Wilson, 2005), available monitoring data, climate change projections (IPCC, 2013), and conditional inference tree (ctree) data analysis (further details in section 2.3, 2.3 and Appendix B; Hothorn et al., 2006). Data were obtained from nine monitoring programmes (Fig. 1; Table A.1). Variables were excluded if ctree data analysis did not reveal significant relationships to other variables (Appendix B). For some potentially relevant biodiversity groups (e.g. fish, marine mammals) or processes (e.g. subtidal blooms of filamentous brown algae and associated beach fouling), no data were available (Appendix B). Climate change projections were incorporated to compare the current state of Dublin Bay with predicted conditions following RCP 4.5 and 8.5. for the period 2081–2100 (IPCC, 2013).

Data analyses were conducted with R Studio version 1.4.1106 (RStudio Team, 2021) and R version 4.1.0 (R Core Team, 2021), using the function *ctree* of the package partykit (Hothorn and Zeileis, 2015), and the libcoin (Hothorn, 2021) and tidyverse (Wickham et al., 2019) packages. The BayesFusion GeNIe Modeler version 3.0.6518.0 was used to implement the Bayesian Network.

2.1. BN structure

The BN comprises 20 variables (Fig. 2, Table C.1), including four 'input nodes' (defined as variables that are not affected by any other variable): (i) 'climate change' to compare the current state of Dublin Bay to predicted conditions following RCP 4.5 and 8.5. for the period 2081–2100 (IPCC, 2013); (ii) nutrient ratio of dissolved inorganic nitrogen to phosphate (DIN: PO_4–P); (iii) nutrient ratio of phosphate to silicate dioxide (PO_4–P:SiO_2); and (iv) sediment organic content. Only climate change can be classified as a driver, whereas the other three input variables reflect abiotic environmental states. For those, quantitative information on the underlying pressures and drivers that produced them was unavailable (e.g. agricultural runoffs or tidal water input from the Irish Sea). The node climate change is linked to more explicit pressures, such as warming, ocean acidification, changes to precipitation patterns and sea level rise. These, in turn, are linked to the intermediate abiotic nodes water temperature, pH, salinity, water agitation, the ecological quality status (EQS) of oxygenation as defined in the WFD, and the areal extent of intertidal sand and mud flats. The
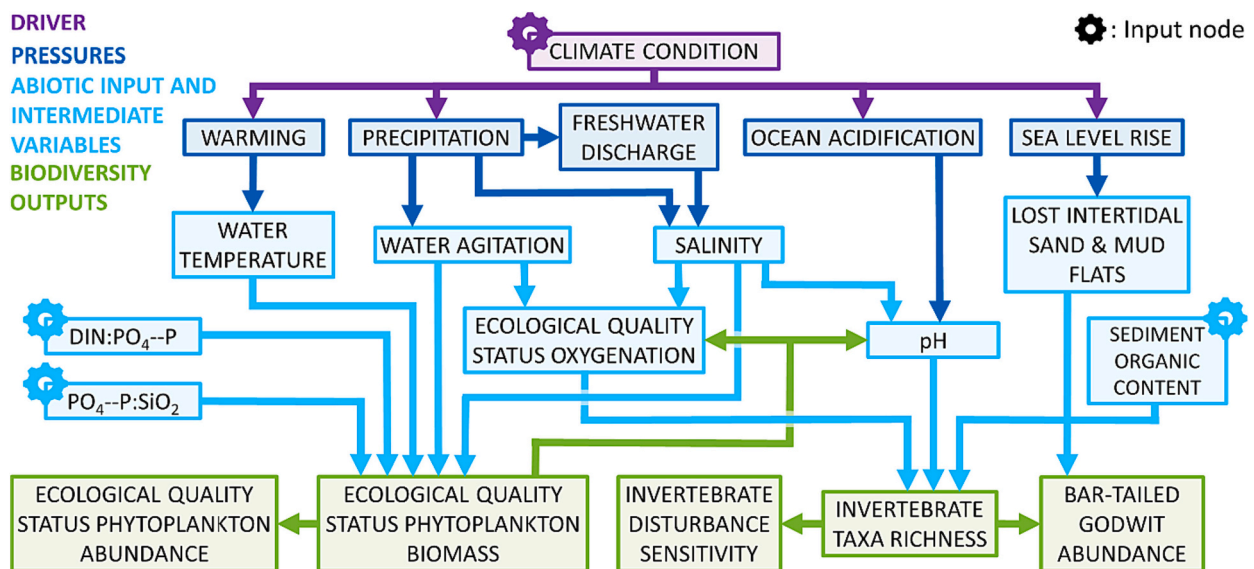

Fig. 2. Bayesian Network of environmental variables and biodiversity of Dublin Bay, including drivers (purple), pressures (dark blue), abiotic variables (light blue) and biodiversity outputs (green). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

abiotic nodes are linked to the condition of five biodiversity indicators, which are the 'output nodes', and include: (i) EQS of phytoplankton biomass; (ii) EQS of phytoplankton abundance; (iii) benthic invertebrate taxa richness; (iv) benthic invertebrate disturbance sensitivity; and (v) the abundance of bar-tailed godwits (*Limosa lapponica lapponica*), which are representative of key wading bird populations.

Bar-tailed godwits were chosen as a biodiversity indicator in the BN because they are exclusively tied to the intertidal zone (Granadeiro et al., 2006). The species is considered 'Near Threatened' in the IUCN Red List (Wetlands International, 2022) and amber-listed as bird of conservation concern in Ireland (Colhoun and Cummins, 2013), with the decline of available intertidal habitat posing a major threat to these waders (Tierney et al., 2017). Peak counts of bar-tailed godwits in Dublin Bay can meet the threshold of international importance, which reflects 1% (> 1500 birds) of the biogeographic population of Northern and Western Europe (Wetlands International, 2022).

2.2. Data analysis

Temporal and spatial resolution, sampling dates and sampling locations differed between the available monitoring data sets (Table A.1) but were matched as closely as possible when merging them for data analysis (Appendix D). Data obtained from different sampling locations and at different dates were treated as independent observations following two considerations: Firstly, the water residence time in Dublin Bay is <3.4 days (O'Boyle et al., 2015), which is less than the minimum temporal resolution of the analysed data. Secondly, the water column is constantly mixed due to inputs from various directions and sources, including tidal hydrodynamics.

We used open-ocean projections of ocean acidification (IPCC, 2014; Table C.1) as best available estimates, being aware that coastal dynamics and developments under climate change are largely unclear and underlie a complex multitude of drivers (Duarte et al., 2013).

Only data of the photosynthetically productive period from March to September 2007–2020 were considered when modelling physico-chemical variables (the input nodes PO_4–P:SiO_2 and DIN: PO_4–P, and the intermediate variables water temperature, salinity, EQS oxygenation, pH) to accommodate existing thresholds on the ecological status of certain water conditions (EPA Ireland, 2006) and to remove confounding effects of seasonal sampling bias (Ní Longphuirt et al., 2016a; O'Boyle et al., 2015).

The variable 'water agitation' was included as a proxy for weather conditions (cloud cover, light intensity), expecting a calm seawater surface during good weather periods and an agitated to turbulent seawater surface during poor weather conditions. Our statistical analysis confirmed that turbulent conditions increased dissolved oxygen, probably because of increased mixing at the water-atmosphere boundary, and additionally decreased primary productivity, presumably because of higher disturbance levels or reduced light availability in more cloudy conditions. Water agitation was calculated as the ratio of wave height to wave length, which reflects wave steepness and indicates the likelihood that waves will break or shoal (Masselink et al., 2011). Wave length was estimated from wave period using an equation for wave celerity at intermediate water depth (Masselink et al., 2011).

'Invertebrate Disturbance Sensitivity' was included as a variable in the BN as an indicator for subtidal benthic soft-bottom invertebrate community composition. It is based on the strong correlation ($p < 0.001$; Pearson's $r = -0.64$) of taxa richness with the percentage of taxa that was assigned to 'Ecological Group I' based on the established indicator classification system: AMBI (AZTI's Marine Biotic Index [Borja et al., 2000]). Ecological Group I taxa are those known to be sensitive to organic enrichment. We found that where fewer species classified as Group I were present in the invertebrate samples, more taxa of Group II were present, which are described as indifferent, and subsequently more of taxa from Group III, which are considered as tolerant to organic enrichment. The remaining groups IV and V contain (second-order)

opportunistic species, which were present in the samples at <10%, or 3%, respectively. Low invertebrate taxa richness correlated strongly with a high percentage of species indicative of pristine conditions, i.e. sensitive to enrichment. Somewhat counterintuitively, a decrease in richness of these particular taxa is recorded as status improvement in the BN because it is correlates with the presence of the sensitive species that are indicative of pristine conditions.

Currently, Dublin Bay has 15 km^2 of intertidal sand and mud flat habitats, which extend over almost 3 km at their widest and are dominated by well-aerated sands apart from muddy habitats in the estuaries and Bull Island lagoon (NPWS, 2015b).When estimating climate change effects of sea level rise on the area of intertidal sand and mud flats, we assumed the persistence of the current urban, artificial embanking of Dublin's coastline. This will prevent coastal retreat and cause 'coastal squeeze' instead of gaining compensating intertidal areas with rising sea levels, and will ultimately cause the loss of intertidal sand and mud flat habitats (Pontee, 2013).

When modelling the effects of intertidal area loss on bar-tailed godwit abundance according to sea level rise predicted for RCP 4.5 or 8.5, we maintained the abundance thresholds for national and international importance that refer to the current bird population. We assume that if the waders cannot establish themselves elsewhere in the bay owing to coastal squeeze, the overall bird population size will decline (Iwamura et al., 2013), which would lead to adjusted thresholds of counts that reflect national and international importance.

To estimate future bar-tailed godwit abundance in Dublin Bay, we applied an equation that describes the general relationship between estuary area and wader abundance in New Zealand (Whelan et al., 2003):

$$ln(maximum\ abundance) = 0.6647*ln(area)–4.457$$

According to the estimated area loss under the climate change projections RCP 4.5 and 8.5, future bar-tailed godwit populations may be reduced to 89%, or 82%, respectively, compared to current maximum abundance. Applying a similar equation that characterises average peak counts of bar-tailed godwits in England as a function of estuary size (average peak count = 0.0789 * estuary size in ha + 13.158 [Prater, 1981]) resulted in an even more drastic population decline to 85%, or 77%, respectively.

2.3. Defining the node states and discretising continuous variables

A total of 63 variable states were defined, with 2–5 states per variable (Table C.1; Fig. E.1). Existing thresholds were adopted where applicable: RCP 4.5 and 8.5 and the magnitude of the corresponding projected changes for the period 2081–2100 (IPCC, 2013; Jacob et al., 2014) informed the states of warming, ocean acidification, precipitation pattern, sea level rise and the associated area loss of intertidal sand and mud flats (decrease – no change – little to strong increase). Thresholds defined by the EU WFD to classify the status of water quality in transitional and coastal waters were used to characterise the EQS of phytoplankton biomass and abundance and water oxygenation (high – good – moderate – poor – bad). Thresholds at which bar-tailed godwits are considered to occur at numbers of national or international importance at a site defined by the Ramsar Convention and applied by Birdwatch Ireland were applied to discretise wader abundance apart from absence or presence. For pH and invertebrate disturbance sensitivity, i.e. the percentage of invertebrate taxa that are assigned to the Ecological Group I according to AMBI, no previous thresholds existed. Therefore, data ranges were determined following visual analysis of histograms (Feld et al., 2020). All remaining continuous variables were discretised into states using ctree analysis (Appendix F), which applies tree-structured regression models (Hothorn et al., 2006). This type of analysis partitions child node data (the case-specific response variable) according to regression-based break points in the parent node data (the case-specific influencing variable(s)). For example, modelling ctree for chlorophyll *a*
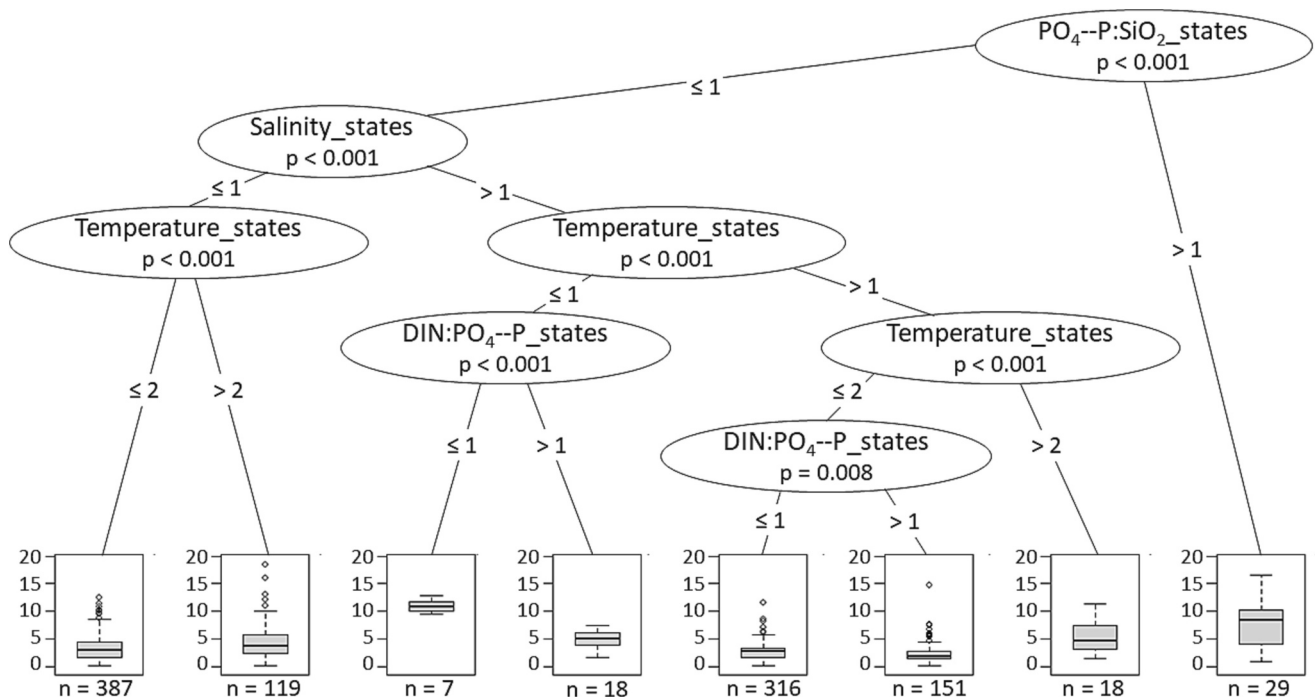
Fig. 3. Conditional inference tree example of modelling chlorophyll *a* concentration as a response of salinity, water temperature and the nutrient ratios DIN:PO$_4$–P and PO$_4$–P:SiO$_2$, applying the previously identified states of those influencing variables. Significant break points in the predictor variables were determined by the model and the response variable data were partitioned accordingly. The boxplots at the bottom of the graph depict the final data partitions including the sample size and the corresponding data distribution of the response variable.

concentration as a response of salinity, water temperature and the nutrient ratios DIN: PO$_4$–P and PO$_4$–P:SiO$_2$ (already applying the previously identified states of those influencing variables) identified child node data chunks, from which the distribution of the respective data across the child node states was extracted (Fig. 3).

In three cases, states of "unknown" data were included to account for limited overlaps of different data sets or for parent node state combinations that could not be matched with child node data (Appendix D).

2.4. Linking nodes and filling the conditional probability tables

Nodes were linked in the BN when ctree analysis indicated significant ($p < 0.05$) partitioning of child node data according to parent node states, i.e. based on significant underlying regression models. Separate analyses were run for all child nodes, i.e. all except for the input nodes, resulting in 32 links (Appendix G). Ctree analysis automatically accounts for non-linear relationships and interactions between variables when it partitions continuous variables into discrete ranges. After defining the node states and identifying statistically significant links, the conditional probability table (i.e. the full crossing of the child node states with all possible parent node states, or state combinations of multiple parent nodes) of each node was filled according to the frequency of the child node state occurring under specific parent node conditions. 946 conditional probabilities were quantified. No predicted probability distributions exist for the states of the climate change pressures sea level rise and acidification, therefore, we linked the predicted magnitude of change with 100% probability of occurrence to the respective climate change scenario. While pH data from recent years were available in the child node of ocean acidification, no probability distribution could be extrapolated for the states of the loss of intertidal sand and mud flat habitats associated with sea level rise, thus, we linked the estimated loss with 100% probability of occurrence to the respective sea level rise scenario. pH and dissolved oxygen conditions that can be expected in an extreme climate change scenario (following RCP 8.5) have not yet been

captured with current monitoring, thus, their effects on invertebrate taxa richness and disturbance sensitivity could not be estimated. Consequently, the corresponding change in wader abundance was estimated exclusively according to the effects of sea level rise and the subsequent loss of intertidal habitat.

2.5. Operating the BN

We ran the model with all possible combinations of input node states (Appendix H), including their general probabilities of occurrence, and present the changes in probability distributions of biodiversity output nodes relative to general current climate conditions in this paper. Probability distributions of invertebrate taxa richness and invertebrate disturbance sensitivity states were scaled proportionally to the amount of available data. Changes in probability distributions of <3% were considered negligible because of the high model uncertainty, following Kelly-Quinn et al. (2022).

2.6. Heuristic validation

To test whether qualitative model performance (network structure and direction of conditional relationships) aligned with expert opinion, a survey with independent experts was conducted. First, a digital survey was completed by nine environmental scientists with direct knowledge of Dublin Bay, where participants were asked to predict relationships among nodes in the BN (Appendix I). Responses were weighted according to the experts' own expertise ratings and transformed into a score (0–1) for consent and disagreement among experts, which was then compared to the model performance (Table I.1). Then, the results were presented to the experts in a 2-h online workshop, during which points of disagreement among the experts and divergence of expert expectation and model performance were discussed. Heuristic consent was reached and no amendments to the BN were required.
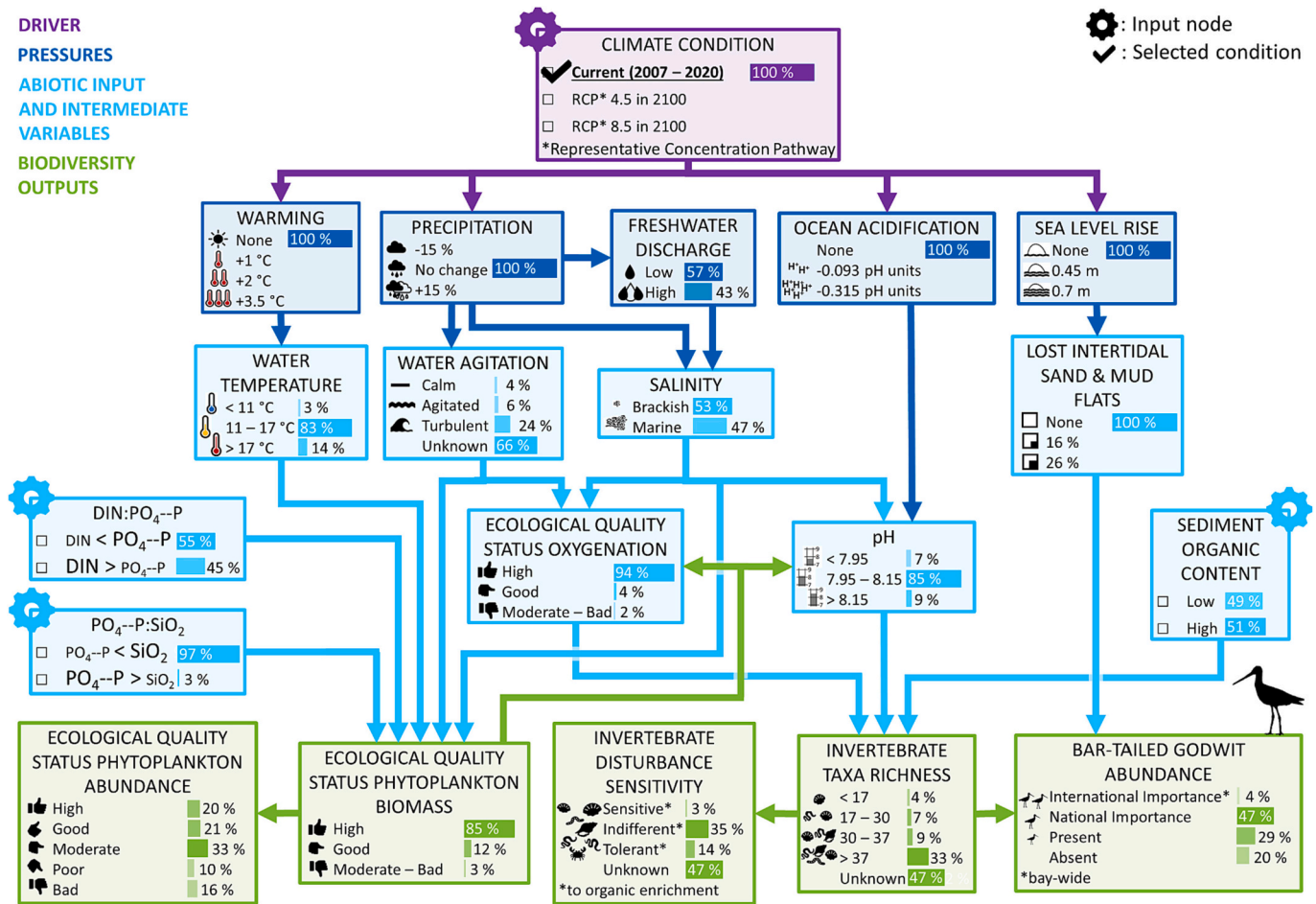
Fig. 4. Bayesian Network of environmental variables and biodiversity of Dublin Bay, node states, and conditional links among them showing the general frequency distributions of the node states as % representing available monitoring data from the years 2007–2020. Drivers (purple), pressures (dark blue), abiotic variables (light blue) and biodiversity outputs (green) are listed from top to bottom. The four input nodes are highlighted by cog wheels. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Results

We built a BN that included climate change scenarios, ratios of DIN:PO$_4$–P and PO$_4$–P:SiO$_2$, and sediment organic content as input nodes, and WFD EQS of phytoplankton biomass and abundance, taxa richness of subtidal invertebrates and their disturbance sensitivity, and abundance of bar-tailed godwits as output nodes. Output node status declined with increasing climate change relative to general current climate conditions, except for invertebrate taxa richness and disturbance sensitivity that improved when sediment organic content was lower (Fig. 4, Table 1).

3.1. EQS phytoplankton biomass

Under current climate and nutrient conditions, the EQS of phytoplankton biomass in Dublin Bay from 2007 to 2020 was classified as 'High' in 85% of observations (Fig. 4). The ratio of DIN: PO$_4$–P affected the EQS of phytoplankton biomass significantly in certain conditions (Fig. 3), however, these conditions did not appear when the full BN was run with climate change as overall input node. When the ratio of PO$_4$: SiO$_2$ was set to SiO$_2$ limitation, a 'High' quality output state of the system was 35% less likely, while the probability of attaining a 'Good' or 'Moderate to Bad' EQS increased by 13% and 22% respectively. These less favourable states became 2–7 times more likely compared to how often they prevailed in 2007–2020 (Table 1). With increasing severity of climate change projections, the model indicated worsening shifts of up

to 14% probability from a 'High' EQS to a 'Good' and, at a lesser extent, 'Moderate to Bad' status (Table 1). Effectively, these less favourable conditions were predicted to be twice as likely than during recent years. PO$_4$–P limitation in the PO$_4$–P:SiO$_2$ ratio mitigated this effect slightly (Table 1). When SiO$_2$ limitation was specified in addition to climate change scenarios, attaining a 'Good' or 'Moderate to Bad' status became equally likely at 27% or 28% probability. This suggests that a 'Moderate to Bad' status is eight times more likely (Table 1).

3.2. EQS phytoplankton abundance

A moderate EQS of phytoplankton abundance was most common in Dublin Bay during 2007–2020, while 'Good' or 'High' status occurred more often than 'Poor' or 'Bad' (Fig. 4). Our model indicated that the EQS of phytoplankton abundance may degrade under SiO$_2$-limited conditions, however, it was not affected by climate change (Table 1).

3.3. Invertebrate taxa richness and disturbance sensitivity

Invertebrate taxa richness was 'High' in 62% of the available observations (Fig. 4) but became 5% less likely when SiO$_2$ was limiting (Table 1). When sediment organic content was 'Low', the probability of state occurrence shifted from 'High' taxa richness to 'Low to Medium' (+28%) and 'Low' (+17%), with the latter effectively becoming three times as likely as during recent years (Table 1). When sediment organic content was 'High', this led to an opposite shift of 5% under additional

Table 1

Conditional probabilities of output node state occurrence with fully crossed input node state combinations from the Bayesian Network of environmental variables and biodiversity of Dublin Bay. General reference conditions from 2007 to 2020 are highlighted in bold on violet background, with light violet (no change, i.e. < 3%), shades of green (improvements) or blue (degradation) illustrate the magnitude of change in probability distributions relative to reference conditions. Colour intensity increases with magnitude of change. States of 'Unknown' data depict incomplete data overlap between available response and predictor variable data. Remaining node states were scaled proportionally to sum up to 100%. Phytoplankton was not linked to sediment organic content and no invertebrate data were available to be extrapolated to RCP 8.5 conditions.

Sediment Organic Content		general			general			general			Low			Low			Low			High			High			High		
Ratio PO_4–P:SiO_2		general			PO_4–P-limited			SiO_2-limited			general			PO_4–P-limited			SiO_2-limited			general			PO_4-limited			SiO_2-limited		
Climate Condition		Current*	RCP 4.5**	RCP 8.5**	Current	RCP 4.5	RCP 8.5	Current	RCP 4.5	RCP 8.5	Current	RCP 4.5	RCP 8.5	Current	RCP 4.5	RCP 8.5	Current	RCP 4.5	RCP 8.5	Current	RCP 4.5	RCP 8.5	Current	RCP 4.5	RCP 8.5	Current	RCP 4.5	RCP 8.5
EQS Phytoplankton Biomass	High	85	-11	-14	+1	-10	-13	-35	-39	-40																		
	Good	12	+8	+10	0	+7	+10	+13	+15	+16																		
	Moderate to Bad	3	+3	+4	-1	+3	+3	+22	+24	+24																		
EQS Phytoplankton Abundance	High	20	-1	-1	0	-1	-1	-4	-4	-4																		
	Good	21	+1	+1	0	+1	+1	+1	+1	+1																		
	Moderate	33	0	0	0	0	0	+1	+1	+1																		
	Poor	10	0	0	0	0	0	+1	+1	+1																		
	Bad	16	0	0	0	0	0	+1	+1	+1																		
Invertebrate Taxa Richness	Low	8	-5		0	-5		+1	-5		+17	+42		+17	+42		+21	+42		-4	-8		-4	-8		-2	-8	
	Low to Medium	13	-3		0	-3		+2	-4		+28	-13		+28	-13		+28	-13		-4	-4		-4	-4		-3	-4	
	Medium to High	17	-1		0	-4		+2	+2		0	-17		0	-17		-5	-17		+1	-1		0	-1		+3	+3	
	High	62	+9		0	+12		-5	+7		-45	-12		-45	-12		-44	-12		+7	+13		+8	+13		+2	+9	
	Unknown (absolute)	47	69	100	47	69	100	46	68	100	88	96	100	88	96	100	83	94	100	9	43	100	9	44	100	11	44	100
Invertebrate Disturbance Sensitivity	Sensitive	6	-3		0	-3		1	-3		+11	+19		+11	+19		+12	+11		-2	-4		-2	-3		0	-4	
	Indifferent	66	+2		0	+2		1	+2		0	-16		0	-16		+4	0		+1	+1		+1	+1		0	+2	
	Tolerant	28	+1		0	+1		-2	+1		-11	-3		-11	-3		-16	-11		+1	+3		+1	+2		0	+2	
	Unknown (absolute)	47	69	100	47	69	100	46	69	100	88	96	100	88	96	100	83	94	100	9	43	100	9	43	100	11	44	100
Bar-tailed Godwit Abundance	Bay-wide International Importance likely	4	-1	-3	0	-1	-3	0	-1	-3	-1	-1	-3	-1	-1	-3	-1	-1	-3	+1	-1	-3	+1	-1	-3	+1	-1	-3
	National Importance	47	-2	-3	0	-2	-3	-1	-2	-3	-2	-4	-3	-2	-4	-3	-2	-4	-3	+1	-1	-3	+1	-1	-3	+1	-1	-3
	Present below thresholds	29	+3	+6	0	+3	+6	+1	+3	+6	+3	+5	+6	+3	+5	+6	+3	+5	+6	-2	+2	+6	-2	+2	+6	-2	+2	+6
	Absent	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Colour code:

Current general probability distribution without specifications [%]

No change (i.e. < 3 %) relative to current general distribution

	3-5 %	6-10 %	11-20 %	21-50 %
Improvement (+)	3-5 %	6-10 %	11-20 %	21-50 %
Degradation (-)	3-5 %	6-10 %	11-20 %	21-50 %

*period 2007-2020   **climate change projections for the year 2100

SiO_2-limitation from the states of lower to high(er) taxa richness, and 8% under general or PO_4–P -limited nutrient conditions (Table 1). Despite the lack of data for RCP 8.5, the model shows that the probability to attain 'High' taxa richness increased by 9% under climate change scenario RCP 4.5 and general sediment organic content, by 7% when SiO_2 and 12% when PO_4–P was limiting (Table 1). Under 'High' sediment organic content, the shifts in the probability distribution under scenario RCP 4.5 almost doubled compared to those observed under current conditions (Table 1). When sediment organic content was specified as 'Low', 'Low' taxa richness was estimated to become six times more likely under RCP 4.5 conditions compared to what was observed in current data (Table 1). Whenever low taxa richness became more likely, the species sensitive to organic enrichment were 3–4 times more likely to occur than observed during recent years, while high taxa richness was associated with higher proportions of species indifferent or tolerant to organic enrichment (Table 1).

3.4. Abundance of bar-tailed godwits

Bar-tailed godwits occurred at numbers of national importance in 47% of the observations, were present below this threshold in 29% of the occasions and absent 20% of the time (Fig. 4). In 4% of the observations, the threshold for international importance was met (Fig. 4), which translates into ten events during the seven years of available data. This is very close to the 12 occasions derived from the raw data (independent of the data handling required for the BN) and indicates that the model estimates may be conservative as to when the threshold of international importance will be met. In both climate change scenarios, nationally important numbers were estimated to occur 2–3% less often in the probability distribution, while presence at numbers below the current threshold for national importance increased by 3–6% (Table 1). Following RCP 8.5 predictions, our model indicated that the abundance of bar-tailed godwits may exceed the threshold of international importance in only 1% of the observed probability distribution, which means a reduction of 75% to only one occasion every 2–3 years (Table 1).

The probability of attaining bar-tailed godwit abundances above the nationally or internationally important thresholds decreased when sediment organic content was 'Low'. While the probability of the waders being present below any threshold increased by 3% in current and by 5% in predicted RCP 4.5 climate conditions (Table 1). 'High' sediment organic content did not affect the probability distribution of wader abundance (Table 1). The effects of nutrient conditions on phytoplankton biomass did not pass through the trophic levels and had no effect on the abundance of bar-tailed godwits (Table 1). Seasonal absence of these waders was similar in all modelling scenarios (Table 1).

3.5. Quantified uncertainty in the BN

All modelled changes in the EQS of phytoplankton biomass can be interpreted with high confidence, because they involve at least 10% of change in the probability distribution (Kelly-Quinn et al., 2022; Table 1). The same applies to most of the climate change predictions for invertebrate taxa richness and to all changes that can be expected in conditions of low sediment organic content, including the corresponding shifts in the invertebrate disturbance sensitivity. In contrast, the very even probability distribution of the five states of the EQS phytoplankton abundance in current conditions and changes according to SiO_2 limitation should be interpreted with caution. This also applies to the small changes (< 5%) in the probability distribution of bar-tailed godwit abundances under low sediment organic content, or in a moderate

climate change scenario (Table 1). All remaining modelled changes in probability distributions are 5–10% and should be interpreted at an intermediate level of uncertainty (Table 1).

4. Discussion

The BN predicts an overall degradation in ecological status of Dublin Bay under the intermediate and extreme (business as usual) scenarios of predicted climate change, which is illustrated by a reduction in four of five proxies for ecological health and biodiversity. Specifically, the WFD EQS of phytoplankton biomass (high status will be 14–17% less likely), invertebrate taxa richness (low taxa richness will be 62% less likely), invertebrate disturbance sensitivity (will be 50% less likely to show pristine conditions), and the abundance of bar-tailed godwits (75% decline of presence at international importance) will all be lower. The EQS phytoplankton abundance was not affected by climate change, but by SiO_2 limitation.

The ratio of DIN: PO_4–P did not affect the biodiversity indicators included in the BN, contrary to intuitive initial expert expectation (Appendix I). DIN limitation occurred in 55% of the observations and PO_4–P-limitation in the remaining 45%, illustrating the alternating states of low and high tides with a periodic pulse supply of PO_4–P from the Irish Sea and continuous supply of riverine DIN inputs (O'Boyle et al., 2015; O'Higgins and Wilson, 2005). Owing to the short residence time of water in the well-flushed Dublin Bay, phytoplankton biomass tends to be low compared to the amount of available DIN and PO_4–P, which indicates export of both nutrients and phytoplankton into the Irish Sea rather than retention within the Bay (O'Boyle et al., 2015). Recent management efforts in Irish river catchments (e.g. reducing fertiliser applications, improving farming practices) have reduced phosphorus levels substantially in freshwater systems (O'Boyle et al., 2016). Nitrogen loadings have decreased to a lesser extent, causing elevated DIN: PO_4–P ratios that may cause shifts in phytoplankton community compositions or opportunistic green macroalgal blooms in estuaries with strong marine influences, which are usually DIN-limited (Ní Longphuirt et al., 2016b; O'Boyle et al., 2016). Macroalgal blooms regularly occur in Dublin's Tolka Estuary, which is at risk of eutrophication from the adjacent urban waste water treatment plant (Jeffrey et al., 1995; Ní Longphuirt et al., 2016a). Additionally, the remineralisation of settled particulate matter inputs from the Irish Sea facilitates macroalgal blooms in Dublin Bay and is considered to be the main cause of the (not monitored) subtidal *Ectocarpus* mats that get washed up on Dublin's beaches in autumn and indicate eutrophic conditions (Jeffrey et al., 1995, 1993; Jennings and Jeffrey, 2005). Reducing nitrogen loads considerably might reduce opportunistic macroalgal blooms, which may be of particular interest if macroalgae in Dublin Bay show similar increased growth as phytoplankton biomass under expected climate change.

Phytoplankton production in Dublin Bay is currently phosphorous limited (97% of the observations from 2007 to 2020) and increases in phytoplankton biomass and corresponding degradation of the EQS phytoplankton biomass can be expected with high certainty under SiO_2-limitation. SiO_2-limitation impairs the growth of diatoms, which are a major food source for primary consumers, such as zooplankton, filter feeders and fish (Officer and Ryther, 1980; Zhang et al., 2020). When diatom growth is limited, flagellates can dominate phytoplankton communities (Howarth and Marino, 2006). Flagellate communities persist longer because they are grazed less heavily and are associated with nuisance events, such as shellfish poisoning, discoloured and malodorous water and hypoxia (Officer and Ryther, 1980). Reduced grazing decreases the flux of organic matter from the water column to the sediment (Howarth and Marino, 2006), which may explain why low invertebrate taxa richness and higher percentages of invertebrate species that are characteristic of pristine conditions became more likely under SiO_2-limitation. While the tidal exchange with the Irish Sea cannot be managed locally, river and sewage treatment discharge,

which are main sources of SiO_2 in coastal systems, hold opportunities for management action to maintain a high EQS of phytoplankton biomass (Zhang et al., 2020). These include maintaining a phosphorous-limited PO_4–P:SiO_2 ratio in effluents or considering the implications that regulating the flow of Dublin's largest river Liffey through up-stream reservoirs may have on the nutrient balance in Dublin Bay.

Invertebrate taxa richness was high in 62% of observations from 2007 to 2020 and became even more likely when sediment organic content was high and PO_4–P limiting. Conversely, low invertebrate taxa richness was most likely to occur when SiO_2 was limiting, and especially when sediment organic content was low. Deposition, decomposition and bioturbation of particulate matter drive sediment organic content, which was almost as often low (49%) as high (51%) from 2007 to 2020, and potentially even productivity and food web complexity in Dublin Bay (Wilson et al., 2002). Even though the tidally-driven input of particulate matter from the Irish Sea has been quantified as ten times more than the combined discharges from rivers and the sewage treatment plant, the latter are considered to fuel localised eutrophication through wind- or wave-driven dynamics (Wilson et al., 2002).

Our data analysis identified a strong negative correlation between invertebrate taxa richness and the percentage of taxa that are indicative of pristine conditions (invertebrate disturbance sensitivity). Increasing taxa richness in combination with an increasing amount of tolerant or even opportunistic species has been shown previously after ongoing disturbance through organic enrichment (Culhane et al., 2019). It is thought that this was because the more sensitive species persisted temporarily before they were replaced by more indifferent and tolerant species. Following the intermediate disturbance theory, high taxa richness may reflect a continuously changing species composition caused by higher rates of disturbance than rates of recovery, which temporarily prevents that competitive exclusion leads to prolonged coexistence (Connell, 1978; Huston, 2014). Increased diversity has also been attributed to higher productivity, which can be caused by increased resource availability through moderate organic enrichment (Huston, 2014; Mittelbach et al., 2001). Consequently, although higher biodiversity is commonly considered as desirable, the community composition should be assessed when evaluating ecosystem functioning or health. Quick changes in taxa richness following disturbance are usually not reflected by summarising indices, such as the Infaunal Quality Index (IQI), that are applied in WFD monitoring to indicate the ecological status of invertebrate communities (Borja et al., 2009; Culhane et al., 2019). This is consistent with the absence of significant links between predictor variables and invertebrate metrics in our analyses, except when we used taxa richness.

Our BN estimated increasing invertebrate taxa richness in the moderate climate change scenario, primarily caused by decreasing pH and oxygenation, i.e. more disturbed conditions. Particularly sea level rise, with its influence on intertidal habitats, has the potential to cause substantial additional changes in benthic macro invertebrate communities (Fujii, 2012), although we lacked data to include such effects in the BN. These communities are pivotal to intertidal, estuarine and coastal food webs because they support higher trophic levels, such as larger crustaceans, fishes and birds (Fujii, 2012). Sea level rise may cause coastal squeeze, which not only causes intertidal habitat loss but may also alter sediment deposition and particle size distribution, the vertical shore profile, the salinity gradient between freshwater and marine conditions, and mixing conditions (Fujii, 2012). All of these consequences may affect intertidal benthic communities and prey availability for higher trophic levels, which aligns with the effect of invertebrate taxa richness on wader abundance as higher trophic level in our BN.

We found that benthic invertebrate taxa richness and disturbance sensitivity were positively linked to bar-tailed godwit abundance, even though the only available invertebrate data originated from subtidal instead of intertidal communities. In the Wadden Sea, bar-tailed godwits regularly prey on polychaetes, such as *Arenicola marina, Hediste diversicolor, Nephtys hombergii, Scoloplos armiger,* and *Lanice conchilega,* in

addition to bivalves, such as *Macoma balthica*, and crustaceans, such as *Carcinus maenas* (Scheiffarth, 2001). Five of these species belong to the AMBI Ecological Group III, which is tolerant to disturbance such as organic enrichment, and the remaining two species belong to group II (Phillips et al., 2014). These ecological groups were more common in Dublin Bay when taxa richness was high, which explains the positive effect of high taxa richness on bar-tailed godwit abundance. High invertebrate taxa richness mitigated negative effects of moderate climate change on bar-tailed godwit abundance, while low invertebrate taxa richness had an enhancing effect, probably reflecting the absence or presence of preferred invertebrate prey species.

Regardless of benthic invertebrate taxa richness, a major threat to migrating wader populations, especially those tied to exclusively sandy and muddy intertidal areas, such as bar-tailed godwits, is habitat loss (Fujii, 2012). Bar-tailed godwits perform extreme annual migrations and as site-faithful waders heavily rely on few staging sites (Battley et al., 2012). In Dublin Bay, bar-tailed godwits are only one of >50 migratory waterbird and seabird species, of which 23 occur at nationally important numbers including three at internationally important numbers, and annual peak counts of up to 35,000 birds can be observed during low tide (Tierney et al., 2017). Most birds spend the winter in Dublin Bay but high numbers in spring and autumn show the importance of the site for migratory passage stops (Tierney et al., 2017).

Dublin Bay is an urban marine ecosystem and its shorelines are almost exclusively artificially embanked (Brooks et al., 2016). Current high tides wash up against these embankments, or even wash over them during storm floods. We predict that sea level rise will lead to coastal squeeze and decrease the current intertidal area by up to 25% (Table 1). Establishing new resting and foraging areas to compensate for those lost to sea level rise, e.g. by enabling coastal retreat locally, is one option of complying with the current SPA conservation objectives to maintain wader abundances in Dublin Bay. As this would put urban infrastructure at risk and is therefore not practical, a crucial measure to conserve Dublin Bay as an important area for waders and to comply as closely as possible with the UNESCO Biosphere conservation objectives is protecting the remaining habitat. Dublin's shorelines, however, are among the most heavily used in Ireland, both for land-based activities and for water sports (Brooks et al., 2016). Already at the current intertidal areal extent, waterbirds are frequently disturbed by human recreational and leisure activities, which causes the birds to move and interrupts their foraging or resting at the cost of energy expenditure (Tierney et al., 2017). Our BN indicates that climate change, including sea level rise, will reduce wader abundance, putting the status of Dublin Bay as an internationally important staging site for far-migrating waders such as the bar-tailed godwits at risk. Consequently, management needs to consider potential conflicts of interest in the both ecologically and culturally important shorelines and intertidal areas and find solutions on how to balance the recreational demands of society with existential requirements of local wildlife (Granadeiro et al., 2006).

5. Conclusion

In summary, our BN showed that during 2007–2020: (i) the ecological quality status of phytoplankton biomass in Dublin Bay was generally high but degraded when silica became limiting; (ii) sediment organic content was positively related to benthic invertebrate richness and the abundance of wading birds; (iii) invertebrate communities were most indicative of pristine conditions when sediment organic content was low; and (iv) climate change simulations showed that the ecological status of Dublin Bay will decline in the future.

The model we present should inform decisions regarding the future management of Dublin Bay. For example, if the aim was to maintain or increase wader populations under current climate conditions, then facilitating increased invertebrate taxa richness and higher organic content in the sediment should be targeted. This, however, would oppose efforts of improving the EQS of phytoplankton and the occurrence of macroalgal blooms. Methods of achieving the best, or at least the most acceptable, balance between these can be explored further using the BN. Conditions prevailing under climate change RCP 4.5 and 8.5 will affect both fauna and phytoplankton EQS negatively with increasing intensity, which emphasises the urgent need for effective climate change mitigation. As long as habitat loss owing to sea level rise cannot be compensated for, we urge that local management should consider how to best protect the remaining habitat of the at-risk biodiversity in Dublin Bay and habitats at other sites along the coast.

This study shows how Bayesian Networks are a useful tool to move beyond direct predictor-response analyses. BNs both assess how a multitude of interacting variables in a complex system influence each other and how the system may respond to various combinations of driving input variables. This study highlights the value of linking existing information from a variety of sources in a way that deepens the understanding of a system, provides context-dependent trajectories, informs reasoning, and facilitates discussion and management decisions on a local level. Parametrising the model also revealed data gaps and the need for concerted and coordinated monitoring programmes. While large quantities of monitoring data exist and are continuously compiled, they are rarely directly compatible across space and time (Dafforn et al., 2016). The WFD launched extensive national monitoring programmes, however, much more concerted monitoring efforts are necessary to capture the full range of ecological processes in Dublin Bay across seasonal and ecologically successive patterns. There remains a lack of quantitative data, e.g., suspended material and deposition, chemical pollution and effects of ship traffic, littering, subtidal macroalgal blooms, intertidal invertebrates, or disturbance of waders through recreational activities including dog-walking. Most importantly, linking the data of monitoring programmes that are conducted in parallel is crucial to deepen a comprehensive understanding of marine systems, such as Dublin Bay, and tracing pressures back to their origin so that explicit management actions can be identified.

CRediT authorship contribution statement

Katrin S.H. Schertenleib: Conceptualization, Methodology, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing. **Michael Bruen:** Conceptualization, Methodology, Writing – review & editing. **Tasman P. Crowe:** Conceptualization, Writing – review & editing. **Nessa E. O'Connor:** Funding acquisition, Supervision, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seares.2023.102442.

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