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Doutorado em Ecologia

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MODELOS ECOLÓGICOS PREDITIVOS PARA AVALIAR OS EFEITOS DA ELEVAÇÃO DO NÍVEL DO MAR EM MACROINVERTEBRADOS BENTÔNICOS ESTUARINOS

Salvador, novembro de 2021

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"Tenho esperança de que um maior conhecimento do mar, que há milênios dá sabedoria ao homem, inspire mais uma vez os pensamentos e as ações daqueles que preservarão o equilíbrio da natureza e permitirão a conservação da própria vida." (Jacques Cousteau).

Eu amava como amava um pescador

que se encanta mais com a rede que com o mar..

(Oswaldo Montenegro).

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Muito obrigado!

Como as mudanças climáticas podem afetar a fauna que vive entre o rio e mar?

YURI COSTA

O tema das mudanças climáticas tem ganhado mais importância uma vez que a humanidade tem experienciado com mais intensidade diversos fenômenos naturais, como chuvas intensas, inundações e secas cada vez mais severas. Estes eventos confirmam as previsões realizadas pelo Painel Intergovernamental sobre Mudanças Climáticas (IPCC - Intergovernmental Panel on Climate Change) que apresentou seu primeiro relatório em 1990. Entre os principais efeitos das mudanças climáticas, a elevação do nível do mar é particularmente preocupante pois terá como consequência a progressiva inundação de grande parte da zona costeira pelo oceano nas próximas décadas. Alguns ambientes de transição como praias arenosas, baías e estuários serão os primeiros a sofrer esses efeitos. Os estuários são ambientes de transição aquáticos entre os rios e o oceano onde ocorre o encontro da água salgada do oceano com água doce do rio, formando o que se chama de gradiente de salinidade. O encontro dessas massas de água com características distintas dá origem a um ambiente importante para a sociedade. O ambiente estuarino abriga uma exuberante fauna (peixes, crustáceos e moluscos) e flora (manguezais e marismas) criando um ecossistema muito importante para manutenção de serviços ecossistêmicos como local de alimentação e berçário para diversas espécies de aves e peixes. Os seres vivos que habitam as águas salobras e sedimentos (areia e lama) de grande parte do estuário são adaptados a viver em um ambiente inóspito para muitas espécies marinhas e de água doce. Dessa forma alterações neste ecossistema, como mudanças no padrão da salinidade, causadas pela elevação do nível do mar, podem alterar a distribuição espacial dos organismos e impactar serviços ecossistêmicos importantes como a pesca. Assim, é extremamente importante que as autoridades como gestores e políticos planejem quais ações devem ser tomadas para minimizar os impactos dos efeitos das mudanças climáticas nos estuários. Para isso, ferramentas que forneçam previsões sobre as respostas ecológicas aos efeitos da elevação do nível do mar são necessárias. Este estudo foi proposto para investigar possíveis estratégias para previsão de efeitos ecológicos das mudanças climáticas sobre os estuários. Após a revisão de diversos artigos científicos que analisaram os efeitos da elevação do nível do mar em estuários, foi observado que a intrusão salina e a inundação são temas centrais. Particularmente a intrusão salina foi o fenômeno ao qual os pesquisadores dedicaram maior atenção. Essa intrusão é o avanço progressivo da água do mar (salgada) em direção ao rio, resultando no aumento da salinidade em regiões onde a salinidade atualmente é mais baixa. Os resultados de modelos computacionais de circulação indicaram que quanto maior a elevação do nível do mar, maior será a penetração da salinidade no estuário, principalmente em condições de redução da vazão dos rios, que pode ser causadas por secas ou construção de barragens. Outro levantamento buscou identificar os principais modelos ecológicos que utilizam a fauna bentônica (animais que vivem no fundo do estuário) como forma de investigar alterações nos ambientes aquáticos. Os resultados indicaram que os pesquisadores têm usado principalmente modelos de distribuição espacial das espécies aplicados a temas como impacto de atividades humanas nos ecossistemas aquáticos (biomonitoramento), potenciais efeitos das mudanças climáticas e introdução de espécies invasoras. Por fim, a presente tese testou uma dessas ferramentas preditivas em um estuário real. Para tal, aplicamos projeções de cenários futuros de elevação do nível do mar para o estuário do Jaguaripe, na Bahia e usamos a modelagem de distribuição de espécies pra avaliar os efeitos ecológicos da intrusão salina na distribuição da fauna bentônica. De modo geral, a resposta da fauna à intrusão salina foi a migração para regiões mais internas do estuário. Isso pode representar uma ameaça ao ecossistema, pois a intrusão salina pode favorecer acesso de muitas espécies marinhas a regiões mais internas do estuário, alterando relações biológicas como a competição e a predação. Concluimos neste estudo que a modelagem de distribuição de espécies pode ser usada para previsão do efeito da intrusão salina sobre a fauna bentônica em estuários. Os modelos ecológicos preditivos devem ser explorados por pesquisadores conjuntamente com gestores para o plenejamento de medidas de mitigação dos impactos das mudanças climáticas nos ecossistemas costeiros.

Resumo

Entre os principais efeitos das mudanças climáticas na zona costeira a elevação do nível do mar é um dos mais relevantes, pois pode levar a inundação, erosão costeira e salinização dos solos e corpos d'agua. Os estuários podem ser os primeiros ambientes a serem afetados pela intrusão salina induzida pela elevação do nível do mar. Alterações no padrão de distribuição da salinidade no estuário podem afetar os organismos (fauna e flora), uma vez que são adaptados a viver neste ecossistema que está sujeito a fortes gradientes (e.g., salinidade, sedimento). Entre os organismos que habitam o estuário, a fauna bentônica tem sido utilizada com sucesso para acessar efeitos ecológicos das alterações nas variáveis físicas do ambiente. Esses organismos tem se mostrado muito úteis também na construção de modelos ecológicos preditivos. Esses modelos podem fornecer valiosas informações sobre quais serão os efeitos das mudanças climáticas e da elevação do nível do mar. Este estudo propõe a i) sistematização dos principais modelos preditivos ecológicos que utilizam a fauna bentônica; ii) compilação e discussão dos estudos que simularam os efeitos da elevação do nível do mar em estuários e iii) simulação do efeito da elevação do nível do mar na distribuição espacial da fauna bentônica em um estuário real, usando modelagem de distribuição de espécies. Foi observado que os principais modelos preditivos aplicados aos organismos bentônicos utilizaram modelagem de distribuição de espécies no monitoramento ambiental para prever impactos causados por atividades humanas, alterações causadas por mudanças climáticas e introdução de espécies exóticas. Recentemente a aplicação de técnicas de machine learning e uso de softwares gratuitos (e.g., R) apontam para o contínuo crescimento deste tópico de pesquisa. A literatura apontou também que os principais efeitos da elevação do nível do mar em estuários são a intrusão salina, as inundações e os efeitos ecológicos destes dois fenômenos. A síntese obtida com dados de modelos numéricos também indicou a influência da descarga dos rios sobre os efeitos diretos da elevação do nível do mar na intrusão salina. Os efeitos ecológicos da intrusão salina e inundação foram estudados principalmente através de experimentos manipulativos ou usando abordagens baseadas em sistemas de informação geográfica (e.g., modelo digital do terreno). Uma vez que modelos hidrodinâmicos numéricos possuem maior acurácia na previsão de tais efeitos, o uso de tais previsões em modelos ecológicos deve ser priorizado. A modelagem de distribuição de espécies foi aplicada com sucesso para previsão dos efeitos da intrusão salina no estuário do Jaguaripe - BA sobre a distribuição espacial de oito famílias de organismos bentônicos. De modo geral o modelo previu a progressiva migração dos organismos para regiões mais internas do estuário através de processos de colonização e extinção local. Essa migração poderá resultar em um efeito conhecido como marinização, causando possíveis desequilíbrios em médio prazo. Este estudo mostrou que os modelos ecológicos preditivos (i) são úteis para compreensão dos impactos ecológicos da elevação do nível do mar em ecossistemas estuarinos na fauna bentônica e (ii) representam uma importante ferramenta para gestores no planejamento de ações mitigatórias.

Palavras-chave: modelos ecológicos preditivos, estuários, organismos bentônicos, modelagem de distribuição de espécies, elevação do nível do mar, mudanças climáticas.

Abstract

Among the main effects of climate change in the coastal zone, the sea-level rise is one of the most relevant as it can lead to flooding, coastal erosion and salinization of soils and water bodies. Estuaries in particular may be the first environments to be affected by saline intrusion induced by sea-level rise. Changes in the salinity distribution pattern in the estuary can affect the organisms (fauna and flora), as they had to adapt to living in this ecosystem that is subject to strong gradients (e.g., salinity, sediment). Among the organisms that inhabit the estuary, the benthic fauna has been used successfully to assess ecological effects of natural or antroppgenic changes. Additionally, these organisms are used in the construction of predictive ecological models that can provide valuable information about the responses to future changes in the estuarine environment, such as sea level rise. This study proposes the investigation of i) the main predictive ecological models that use the benthic fauna; ii) the studies that simulated the effects of sea-level rise in estuaries and iii) to simulate the effect of sea-level rise on the macrobenthic spatial distribution in a estuary using species distribution modeling. The main predictive models applied to benthic organisms used species distribution modeling in environmental monitoring to predict human impacts and alterations caused by climate change and introductions of exotic species. The use of well-established approaches, the incorporation of machine learning techniques and the use of open-source software (e.g., R) contributed to the growth of this research topic. The main sea-level rise effects in estuaries were saline intrusion, flooding and the ecological effects associated with these two phenomena. The synthesis obtained with data from numerical models indicated a direct effect of sea-level rise on saline intrusion and highlighted the influence of river discharge. The ecological effects of saline intrusion and flooding have been studied primarily through manipulative experiments or using approaches based on geographic information systems (e.g., digital elevation models). Since numerical hydrodynamic models are more accurate in predicting such effects, the use of such predictions in ecological models should be encouraged. Species distribution modeling was successfully applied to predict the saline intrusion effects on the spatial distribution of eight families of benthic invertebrates in the Jaguaripe estuary. In general, local extinction and colonization processes resulted in migrations to the estuary innermost regions. These migrations can result in an effect known as estuary marinization and may cause important environmental changes as saline intrusion advances. This study showed that predictive ecological models are useful for understanding the ecological impacts of sea-level rise in estuarine benthic fauna and are an important tool for managers in planning mitigation actions.

Keywords: predictive ecological models, estuaries, benthic organisms, species distribution modelling, sea level rise, climate change.

Sumário

Estrutura da Tese

A presente tese está estruturada em Introdução geral três capítulos e Conclusões como segue:

Capítulo I – **General trends after forty years of predictive models applied to benthic macroinvertebrates from marine, estuarine and freshwater environment**

O primeiro capítulo é uma revisão sistemática da literatura e aborda os principais modelos ecológicos preditivos usados para investigar a resposta dos organismos bentônicos a alterações das variáveis físicas do ambiente. Neste capítulo foram levantados estudos preditivos realizados nos diferentes ambientes (i.e., marinho, estuarino e de água doce), avaliadas quais foram as principais abordagens, métodos e softwares utilizados.

Manuscrito a ser submetido ao periódico ***Scientometrics***

Capítulo II – **Trends of sea-level rise effects on estuaries: A qualitative and quantitative synthesis towards for a simple general model to estimate future saline intrusion in estuaries**

O segundo capítulo é uma revisão sistemática da literatura e aborda os principais efeitos da elevação do nível do mar sobre os ecossistemas estuarinos. Os efeitos do nível do mar sobre o estuário foram investigados sob os pontos de vista quantitativo e qualitativo. Sob o ponto de vista quantitativo foi realizada uma síntese dos resultados dos modelos preditivos que investigaram a intrusão salina no estuário. Sob o ponto de vista qualitativo foram levantadas informações sobre a distribuição dos estudos no mundo, quais os principais impactos físicos (alteração da salinidade, transporte se sedimentos e temperatura), econômicos (salinização de aquíferos) e ecológicos (perda de biomassa, exclusão de espécies, espécies exóticas) indicados pelos estudos.

Manuscrito a ser submetido ao periódico ***Marine Environmental Research***

Capítulo III - **Sea-level rise effects on macrozoobenthos distribution within an estuarine gradient using Species Distribution Modeling**

O terceiro capítulo trata da simulação da resposta da fauna bentônica aos efeitos da intrusão salina em diferentes cenários de elevação do nível do mar no estuário do Rio Jaguaripe, Bahia.

Manuscrito a ser submetido ao periódico ***Ecological Informatics***

Introdução geral

Alterações climáticas são processos causados principalmente pela variação de gases de efeito estufa (e.g., CO_2 e vapor de água) na atmosfera (Moss et al., 2010). Desde os primeiros relatórios emitidos pelo IPCC (Intergovernamental Panel on Climate Change) a partir de 1990, alertava-se sobre a influência que atividades humanas (e.g., agricultura, indústrias) poderiam exercer sobre alterações no clima do planeta (Rahmstorf et al., 2007). O relatório mais recente do IPCC atesta como inequívoca a influência de atividades humanas sobre a aceleração do processo de aquecimento global (IPCC, 2021).

O aumento da temperatura global possui diversos desdobramentos preocupantes para humanidade como o aumento de eventos extremos (e.g., como chuvas fortes, tempestades, inundações, secas intensas e prolongadas) (Nicholls et al., 2011). Outro efeito direto da elevação da temperatura global é o derretimento das geleiras, que resulta em elevação do nível dos oceanos e pode levar a inundação de grande parte das zonas costeiras ao redor do globo (Allison et al., 2009; Nicholls and Cazenave, 2010).

Cerca de 80% da população mundial vive em cidades litorâneas e diversas atividades importantes são desenvolvidas na zona costeira, grande atenção tem sido dada ao efeito da elevação do nível do mar (Hallegatte et al., 2013; McGranahan et al., 2007). Entre as principais ameaças da elevação do nível do mar estão a inundação permanente do território, salinização do solo e aquíferos. Gerando grandes prejuízos econômicos e sociais (Nicholls, 2011).

Ambientes de transição como praias arenosas, baías e estuários então entre os primeiros ambientes a sofrer com os impactos da elevação do nível do mar (Prandle and Lane, 2015; Ross et al., 2015). Os estuários são especialmente sensíveis à elevação do nível do mar uma vez que este fenômeno pode resultar em modificações no regime de circulação, afetando a estratificação e distribuição da salinidade (Mohammed and Scholz, 2018). Outros efeitos estão associados a mudanças na dinâmica de erosão, transporte de nutrientes, poluentes e patógenos (Prandle and Lane, 2015; Robins et al., 2016). Estas alterações podem afetar importantes serviços (e.g., pesca, navegação, estocagem de carbono) desempenhados pelos estuários e ecossistemas fortemente associados como manguezais e marismas (Donato et al., 2011; Ewel et al., 1998; Lee, 2008; Lee et al., 2014).

O principal impacto causado pela elevação do nível do mar está associado com a salinidade dos estuários que, por definição, são ambientes cuja principal característica é a diluição da água oceânica pela água doce dos rios (Pritchard, 1967). Devido a essa diluição é formado um gradiente de salinidade, que representa a variação da salinidade da região oceânica (média 35 psu) até a montante, onde a salinidade da água é próxima a zero (Day et al., 2012). Com a elevação do nível do mar é esperado que ocorra a intrusão salina, que representa a progressiva entrada de água mais salgada oriunda da região oceânica para regiões mais internas do estuário (Serrano et al., 2020).

A intrusão salina é um dos principais parâmetros usados para avaliar a sensibilidade de estuários à elevação do nível do mar (Prandle and Lane, 2015). Os estudos que avaliaram a sensibilidade de diversos estuários no hemisfério norte indicaram que os maiores impactos serão percebidos em estuários rasos (profundidade média em torno de 10 m), que possuem forte influência da maré e que estejam sujeitos a redução da vazão do rio (Prandle and Lane, 2015; Robins et al., 2016; Serrano et al., 2020).

Do ponto de vista ecológico, a salinidade é a principal variável que influencia a distribuição espacial de organismos da fauna e flora ao longo do estuário (Attrill and Rundle, 2002; Barros et al., 2012; Costa et al., 2015; Gogina and Zettler, 2010a; Whitfield et al., 2012). Em particular, a fauna de invertebrados bentônicos apresenta a sua distribuição espacial fortemente influenciada pela salinidade (Barros et al., 2012; Ysebaert et al., 2003). Essa relação é explicada em boa parte pela origem marinha dos organismos, que desenvolveram estratégias adaptativas (e.g., tolerância à baixa salinidade) e comportamentais (e.g., construção de tubos e galerias) para habitar um ambiente sujeito a variações na salinidade em função da maré (Barros et al., 2012; Beesley et al., 2000; Remane and Schlieper, 1971; Telesh et al., 2013a).

Outro fator que influencia a distribuição espacial da fauna bentônica nos estuários é o padrão de distribuição do sedimento (Little et al., 2017b). Os organismos podem possuir afinidade por diversos tipos de sedimento (e.g., cascalho, areia e lama) (Anderson, 2008; Barnes, 1989). Esta afinidade pode estar relacionada com os traços biológicos (e.g., modo de alimentação, locomoção, reprodução) de cada espécie (Beauchard et al., 2013; Fauchald, 1977; Otegui et al., 2016).

Devido a os organismos bentônicos apresentarem respostas previsíveis a diversas variáveis ambientais como matéria orgânica e poluentes (Egres et al., 2019; Krull et al., 2014; Pearson and Rosenberg, 1978; Tagliapietra et al., 2012; Villeneuve et al., 2018), possuírem mobilidade reduzida e longos ciclos de vida, esses organismos são amplamente usados como ferramentas de monitoramento de alterações ambientais (Borja et al., 2013; Bremner et al., 2006; Dolédec and Statzner, 2008).

Respostas previsíveis é um pré-requisito importante para elaboração de modelos preditivos (Jørgensen and Bendoriccihio, 2011). Esses modelos podem ser usados para prever quais efeitos de alterações ambientais sobre parâmetros ecológicos (e.g., distribuição, abundância e riqueza) das comunidades da fauna bentônica (Attrill, 2002; Gamito et al., 2010; Martins and Marques, 2011).

Os modelos ecológicos preditivos podem ser ferramentas úteis para compreensão da resposta da fauna bentônica a alterações no padrão de salinidade como resultado da intrusão salina forçada pela elevação do nível do mar. Esse tipo de ferramenta pode fornecer informações valiosas pra o planejamento de ações mitigadoras dos efeitos da elevação do nível do mar em estuários, contribuindo para melhor gestão desses ecossistemas (Müller, 1998; Reiss et al., 2015).

Objetivo Geral

O objetivo desta tese é investigar através de modelos ecológicos preditivos quais as respostas dos organismos bentônicos aos efeitos da elevação do nível do mar em estuários.

Objetivos específicos

1. Identificar as principais abordagens, métodos e ferramentas usadas para criação de modelos ecológicos preditivos aplicados aos organismos bentônicos.
2. Sintetizar qualitativa e quantitativamente os principais efeitos da elevação do nível do mar sobre os estuários por meio de revisão da literatura.
3. Simular a resposta da fauna bentônica aos efeitos da intrusão salina em diferentes cenários de elevação do nível do mar no estuário do Rio Jaguaripe, Bahia.

Metodologia Geral

Área de estudo

O estuário do Rio Jaguaripe é raso (profundidade média inferior a 10 m), com circulação dominada pelas marés e representa um dos principais tributários da Baía de Todos os Santos. Possui área de superfície de 2.200 km² e vazão média mensal de 28 m^3s^{-1} (Cirano and Lessa, 2007) e máxima de ($Q = 363\ m^3s^{-1}$) (SNIRH, 2019).

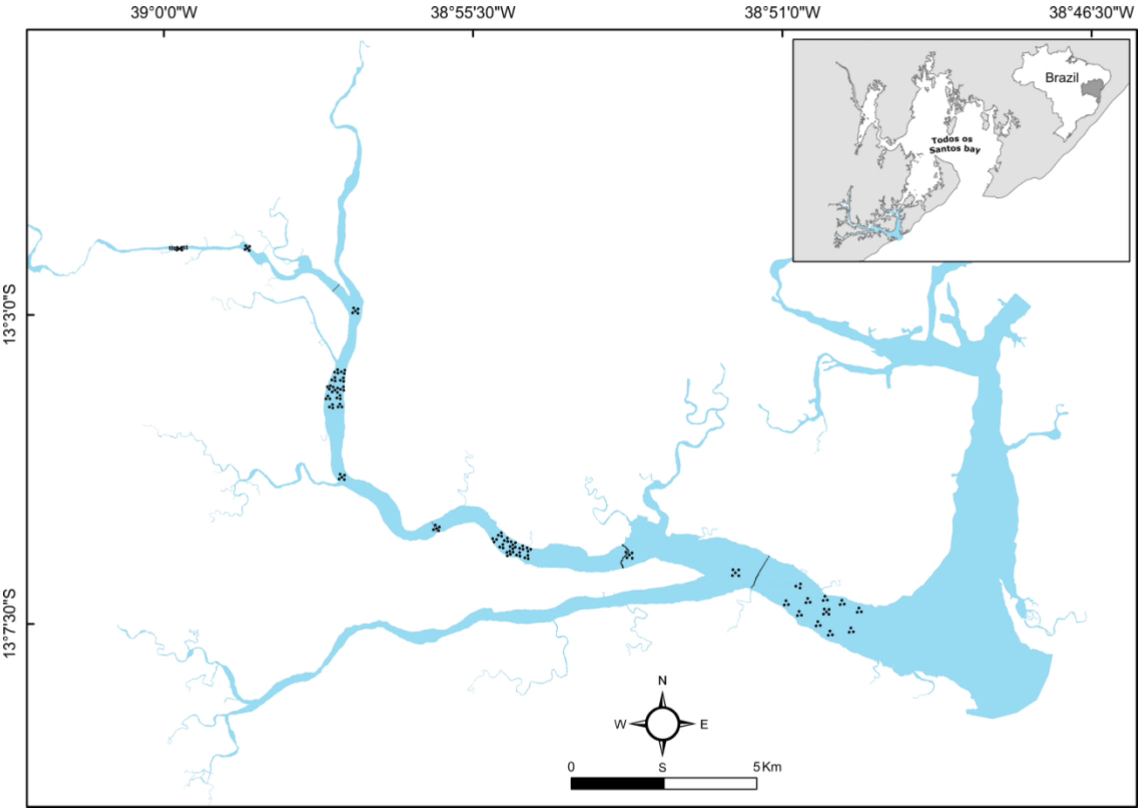

Figura 1. Pontos de amostragem do programa de monitoramento do estuário do Jaguaripe. Foram cinco campanhas realizadas em 10 pontos e uma campanha realizada em quatro regiões ao longo do gradiente longitudinal estuarino e duas campanhas realizadas em quatro regiões ao longo do gradiente transversal (ou seja, entre as margens).

Dados usados na modelagem

Os dados usados neste estudo são oriundos dos trabalhos realizados pelo Laboratorio de Ecologia Bentônica da UFBA nos estuários da Baía de Todos os Santos. As amostras da macrofauna bentônica foram coletadas entre 2006 e 2019 em oito campanhas de coleta. Os locais para amostragem biológica e ambiental (ou seja, sedimento e salinidade) foram visitados várias vezes ao longo dos últimos anos (dados biológicos disponíveis em (Barros et al., 2021)).

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Capítulo 1

General trends after forty years of predictive models applied to benthic macroinvertebrates from marine, estuarine and freshwater environment

Manuscrito submetido ao periódico ***Scientometrics***

General trends after forty years of predictive models applied to benthic macroinvertebrates from the marine, estuarine and freshwater environment

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Abstract

Ecological modeling of benthic fauna is a research topic that emerged about 40 years ago. Researchers in marine, estuarine and freshwater environments have produced predictive models using different strategies (i.e., approaches, methods and software). To understand how this research topic evolved in terms of its practices (i.e., modeling methods and tools) and to identify future trends, a systematic literature review was carried out using the Web of Science platform. We retrieve 969 articles, of which 206 were selected for review and the results suggest that the most recurrent approaches were Species Niche Modeling, Bioassessment and Trophic Web Model. The most popular software were R, Matlab, Ecopath, Maxent, FORTRAN, SPSS, WEKA, ERSEM, SAS, Stella, Excel, AUSRIVAS, and RIVPACS. There was a considerable number of articles that did not indicate software (16%) used in their models. The dominance and growth of free software (e.g., R) is a trend also seen in other fields of ecology. The growing number of implementations from software widely used in many approaches (e.g., Ecopath, Maxent, Stella and Streambugs) for R packages tends to increase the popularity of this software and will likely establish it as the main software for predictive modeling in ecology. Predictive modeling of benthic fauna has its growth strongly associated with computational development and can be an important tool for resources management based on prediction of anthropogenic impacts, invasive species and climate change.

Keywords: Ecological models; Benthos; aquatic environment; R; Machine Learning

Introduction

The understanding of the spatial distribution, composition and abundance of benthic organisms are key to determine the quality of aquatic environments and to improve management (Šiaulys and Bučas, 2012). Furthermore, to design good management strategies it is necessary to take into account possible future changes in the aquatic environment (Reiss et al., 2015). Faced with environmental changes driven by natural disturbances and human impacts, benthic community ecologists are frequently challenged to provide models to predict biological responses (Carvalho et al., 2015; Jørgensen and Bendoriccihio, 2011). For instance, future climate change scenarios, interactions with different environmental impacts (e.g., pollution, biological invasion) and its mitigations are important research topics (Duarte et al., 2020). In fact, several ecological models using benthic fauna have been developed to predict potential environmental changes and provide tools for decision-making on important topics such as invasive species management (Munguia et al., 2010; Zhang et al., 2019), creation of Marine Protected Areas (Gorman et al., 2017; Patrizzi and Dobrovolski, 2018), establishment of long-term environmental monitoring (Reiss et al., 2015) and species distribution scenarios (Meißner et al., 2014; Moraitis et al., 2019; Weinert et al., 2016).

During the last four decades, benthic ecologists working on aquatic environments (i.e., marine, brackish and freshwater) incorporated several modeling technics from other scientific fields (Schlüter et al., 2019). For instance, models that seek to understand systems dynamics through differential equations have a conceptual foundation in mathematics and applications in physics and engineering (Goddard, 1957; Poole, 1936). In benthic ecology these models are used to estimate population and community dynamics (Angulo et al., 2017; Hughes, 1984; Olive, 1992), species dispersion (Jacobsen et al., 1990; Yearsley and Sigwart, 2011), secondary production (Ehrnsten et al., 2020; Rowe et al., 1997) and energy flow between trophic levels (Paillex et al., 2017; Schuwirth et al., 2008). Similarly, other methods such as Fuzzy Inference Systems originally developed to solve logic and computer programming problems (Maddox, 1983; Zadeh, 1965) can be applied in environmental monitoring (Marchini and Marchini, 2006) and habitat suitability (Theodoropoulos et al., 2018). Moreover, the incorporation of techniques from other scientific fields is a natural process (Pickett et al., 2013).

The accelerated growth of computational sciences applied in the ecological context has resulted in a large number of techniques and algorithms used for ecosystem management and for advances in theoretical ecology (Guo et al., 2015). Since ecology is increasingly becoming a quantitative and computational science (Petrovskii and Petrovskaya, 2012; Touchon and McCoy, 2016), a continuous critical assessment of the available and routinely applied methods for ecological modeling is necessary (Austin, 2007) to give a global perspective of the development trends in approaches and techniques (Guo et al., 2015). This will avoid seeking solutions for problems which we already have good tools to solve (Jørgensen and Bendoriccihio, 2011), allows models performance comparisons (Elith and Graham, 2009), improvement of the available techniques and help to orient novel research groups (Austin, 2007; Guo et al., 2015). Considering that ecologists dedicated to the study of benthic fauna have developed studies in different environments (freshwater, estuaries and marine) it is expected that the most used modeling approaches and techniques used in these environments would be different (Constable, 1999; Zhang and Liu, 2012). Different research groups may also use different approaches, techniques and methods due to inherent demands and expertises when addressing different issues (e.g., water quality monitoring and fisheries resources management) (Johnson and Hallstan, 2018; Ortiz and Stotz, 2007). Thus, creating their own modeling culture and a tool kit possibly restricted to their context and environment (Wenger-Trayner, 1998). For instance, in freshwater modeling, some approaches were derived from environmental monitoring protocols developed by managers from government regulatory agencies (Stalnaker et al., 1995) while in the marine environment modeling is frequently related with theoretical ecology hypothesis tests and scenarios simulations such as larval dispersion (Lal et al., 2020), biomass variation (Zhou et al., 2009) and climate change effects on species distribution (Weinert et al., 2016). Therefore, it would be very insightful to describe and compare tools used by researchers working in different aquatic environments which can lead to incorporation of new technique to answer specific questions in innovative and better ways (Jørgensen and Bendoriccihio, 2011; Pickett et al., 2013).

There are few methodological review papers on benthic fauna modeling focusing on pattern description using statistical tools (e.g., Carvalho et al., 2015; Constable, 1999) and predictive modeling (e.g., Reiss et al., 2015). However, there are no assessments considering different predictive model classes (e.g., mathematical, statistical, computational, etc.) at different aquatic environments (i.e., freshwater, brackish and marine) simultaneously. Thus, the aim of this systematic literature review is to provide an overview of the main approaches and tools available for predictive ecological modeling of benthic fauna and how they evolved over time. This review does not intend to provide detailed technical explanations of the numerous modeling techniques. Instead, provide a road map of the modeling strategies associated and their different purposes, highlighting the most used strategies and tools (i.e., approaches, methods and software), as well the environment in which the approaches and tools were most frequently used.

Methods

In order to synthesize the main predictive models applied to benthic macroinvertebrates, we conducted a systematic literature review. The reporting of this systematic literature review was guided by the standards of the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) Statement. PRISMA is a guideline that helps researchers to report more clearly the methodology applied in systematic reviews (i.e., information source, eligibility criteria, selection of included studies, data extraction and analysis) in order to make it more transparent and reliable (Moher et al., 2009; Sarkis-Onofre et al., 2021). The main steps in the classification of studies for this systematic review are depicted in **Fig 1**. Studies were identified in the Web of Science database in December 2020 applying the limit date from 1945 to 2020, using the following search terms: ((model* OR simula*) AND (benth* OR macrozoobenth* OR macrobenth OR macroinvertebrates OR invertebrates) NOT (Benth OR Bentham OR Bentheim OR Bentheimer OR BENTHEM OR BENTHIOCARB OR benthamii OR benthamiana)). The terms included after the 'NOT' boolean operator were used to avoid records not related to the benthic fauna.

A total of 969 records (i.e., papers) were retrieved from the *Web of Science* platform database, no duplicate articles were identified. After reading the titles and abstracts and applied the screening criteria, 681 documents were excluded, and 288 were kept. Among these records, 82 articles were excluded because they are not predictive models (statistical models, n = 49; mathematical models, n = 33) but were descriptions of patterns and processes in which benthic fauna were studied. Thus, our review was conducted with 206 articles (**Fig 1**).

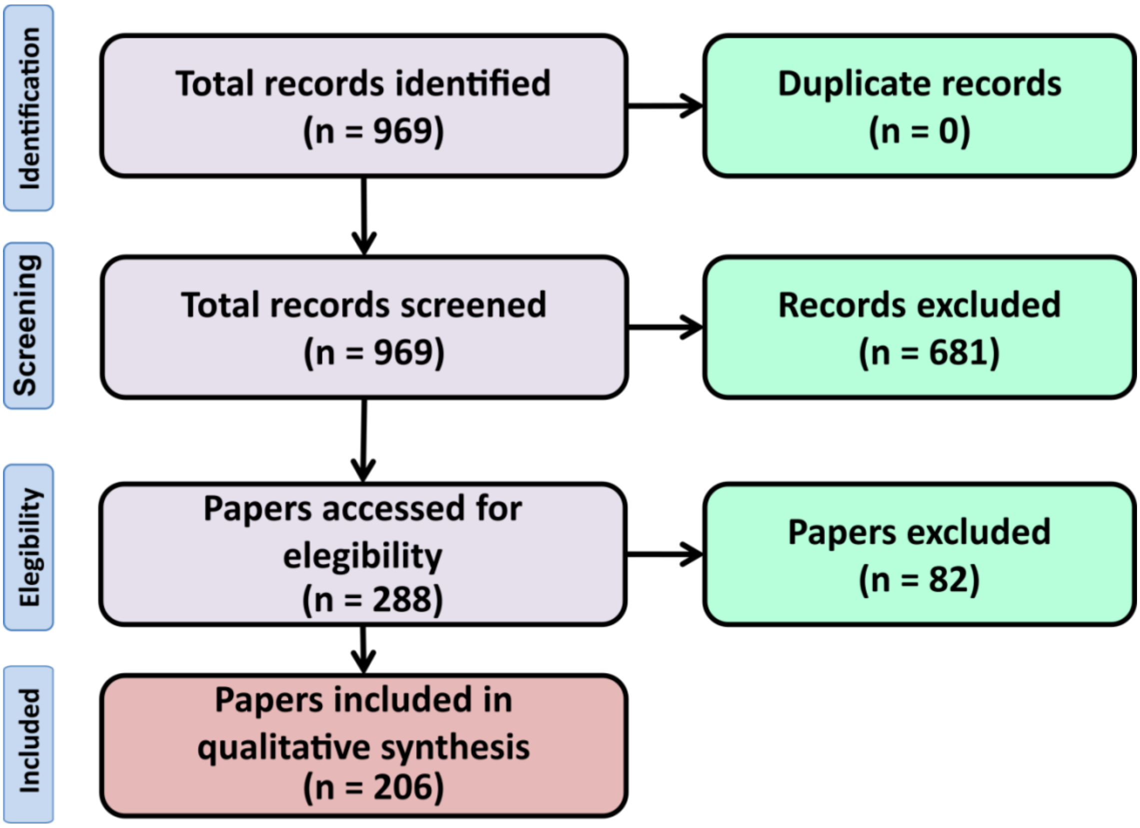

Fig 1 PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram indicating the number of records retrieved in the search, articles evaluated for eligibility and documents included in this review after applying screening criteria

After obtaining the search result, the files were screened on Web of Science platform and the following screening criteria were applied i) had predictive modeling as their objective; ii) used the aquatic environment (i.e., marine, freshwater or brackish water) as an ecosystem model and iii) used benthic invertebrate fauna at different levels of ecological organization (e.g., individuals, populations or communities). Consequently, studies that, for example, which aimed to model the benthic environment (i.e., sea floor) without including fauna and flora in the model, developed predictive models for other groups of invertebrates (e.g., butterflies) outside the aquatic environment were excluded. Documents considered eligible were read in full and those that did not match with the aforementioned inclusion criteria were excluded. Finally, the articles (n = 206) were read to extract the relevant information for our study.

The variables extracted from articles were related to manuscript identification (e.g., year of publication, title and authors), environment (e.g., fresh water, marine or brackish water), ecosystem (e.g., rivers, lakes, estuaries, bays, ocean floor), biological model (e.g., individuals, populations or community) and ecological modeling objective. Related to the models were extracted information about model class (e.g., statistical, mathematical, computational), modeling strategy (i.e., approach, methods, techniques, software and the algorithm used to perform the modeling). Finally, information about the model's evaluation and methods used for validation were extracted. All of this information was compiled into an electronic spreadsheet available in Costa, (2022).

Data analysis

The categories were created based on the information synthesis extracted from the articles after filling in 30% of the retrieved records (about 60 documents). Since the level of detail reported by the authors was quite different, the information was initially recorded at the most detailed level indicated by the authors, and then the categories were created with the aid of information from the literature and based on the most compatible level among the studies. For instance, the main modeling approaches were grouped into eight categories according to the author's purpose. The categories included studies of Species Distribution Modeling, Bioassessment, Trophic Web Model, Dispersion-Colonization, Population Dynamics, Secondary Production, Ecotoxicological studies and Ecological Functions.

We evaluated the evolution in the number of publications obtained from articles frequency published by year and a cumulative curve was built. The most relevant study categories were determined. For this, each variable, frequency value was obtained based on the number of unique records in each category. The categories of each variable were ranked according to their frequency and those that occurred in more than one article were maintained (freq.> 1). To assess the relationship between the categories of the different variables, an alluvial diagram was produced from the matrices of variables. Alluvial diagrams uses streamlines to connect nodes assigned to clusters (variables) in different networks. This approach can be used to investigate relationships between sets of bipartite networks (Rosvall and Bergstrom, 2010). The alluvial diagram was performed using the '*sankeynetwork*' function of the networkD3 package (Allaire et al., 2017) of the R software (R Development Core Team, 2016).

Results

Research Topic Evolution

Overall, predictive ecological modeling applied to benthic fauna is an emerging research topic (**Fig 2**). From the first studies, there was a clear increase in the number of publications around the 1990s (**Fig 2**). We discussed the research topic evolution considering four different phases (i.e., Phase 1: from 1977 to 1989; Phase 2: 1990 - 1999; Phase 3: 2000 - 2009; Phase 4: 2010 - 2020). Thus, it is possible to identify and compare the main changes in the use of approaches and tools in different environments over decades as well as identify similarities in the use of those tools and future trends.

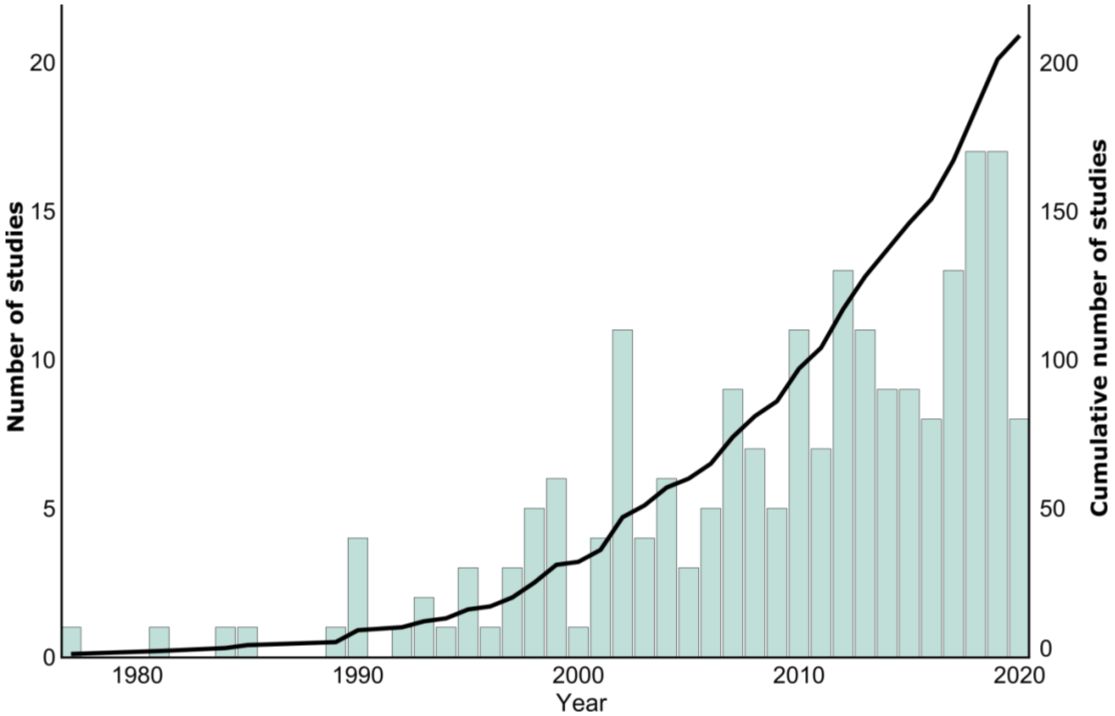

Fig 2 Predictive ecological models applied to benthic fauna between 1977 and

2020. The annual number of publications is represented in absolute values (bars) and accumulated (curve)

In the first phase (1977-1989), five studies were carried out mainly in the marine (40% of total studies in the first phase; n = 2) and freshwater (40%; n = 2) environments, only one study was registered in the estuarine environment. The first study retrieved (Levinton and Lopez, 1977) used the Secondary Production approach (**Fig 3**). Through logistic equation the authors built a model for predicting the carrying capacity based on resource consumption and intraspecific competition of a snail population (*Hydrobia minuta*) in an estuary. The most used approach for modeling was Bioassessment (40%; n = 2) being applied both in the marine environment and in freshwater. Other approaches such as Population Dynamics, Species Distribution Modeling and Secondary Production were also applied in this first phase (**Fig 3**). The most used method was Regression Models (40%; n = 2) and other methods such as Differential Equations and dimensionality reduction techniques such as Multiple Discriminant Analysis were applied (**Fig 4**). The software used were Fortran and PHABSIM (Physical Habitat Simulation) (**Fig 5**). There was a program developed to carry out the Neutral model and two studies in which the software was not indicated.

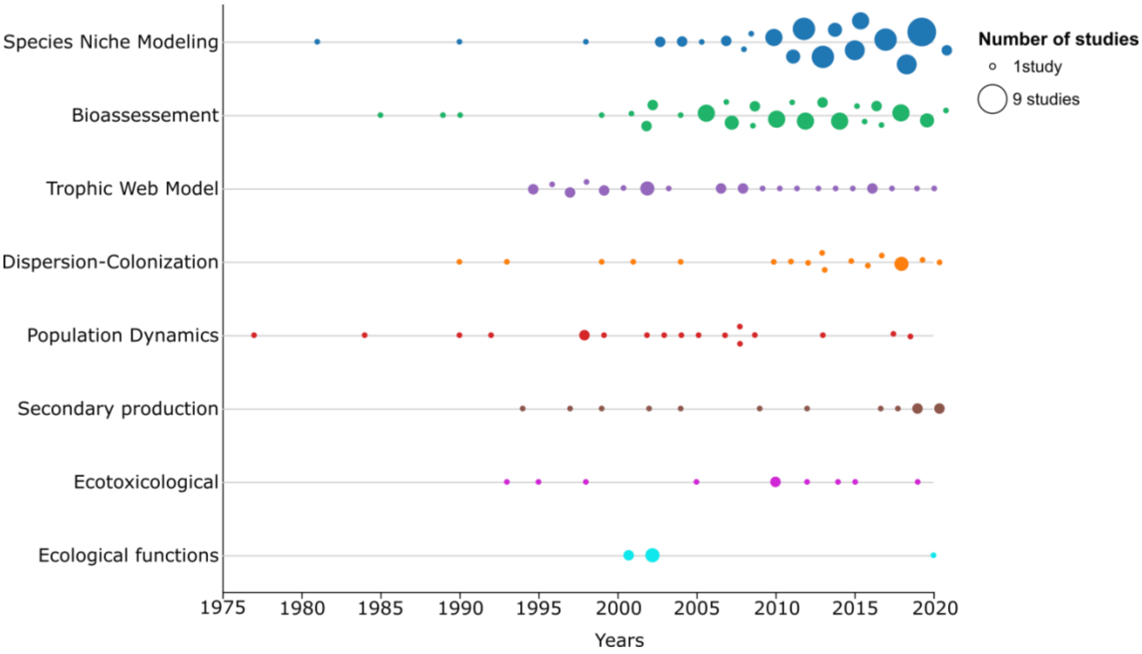

Fig 3 Evolution of the main approaches used for modeling benthic fauna over the four decades

In the second phase (1990-1999), 25 studies were carried out mainly in the marine (44% of total studies in the second phase; n = 11) environment, followed by freshwater (32%; n = 8) and brackish water (24%; n = 6). The most used approach for modeling were both Trophic Web Model (28%; n = 7) and Population Dynamics (20%; n = 5), Dispersion-Colonization (12%; n = 3), Secondary Production (12%; n = 3), Ecotoxicological studies (12%; n = 3), Bioassessment (8%; n = 2) and Species Distribution Modeling (8%; n = 2) were also recurrent (**Fig 3**). The most used method was Differential Equation (60%; n = 15), Regression Models (20%; n = 5) and Individual Based Models (8%; n = 2) were the most recurrent (**Fig 4**). Among eleven software used in this phase, the most recurrent were FORTRAN (16%; n = 4), ERSEM (12%; n = 3) and Stella (8%; n = 2). In eight studies (32%) there was no indication of the software used in the modeling (**Fig 5**).

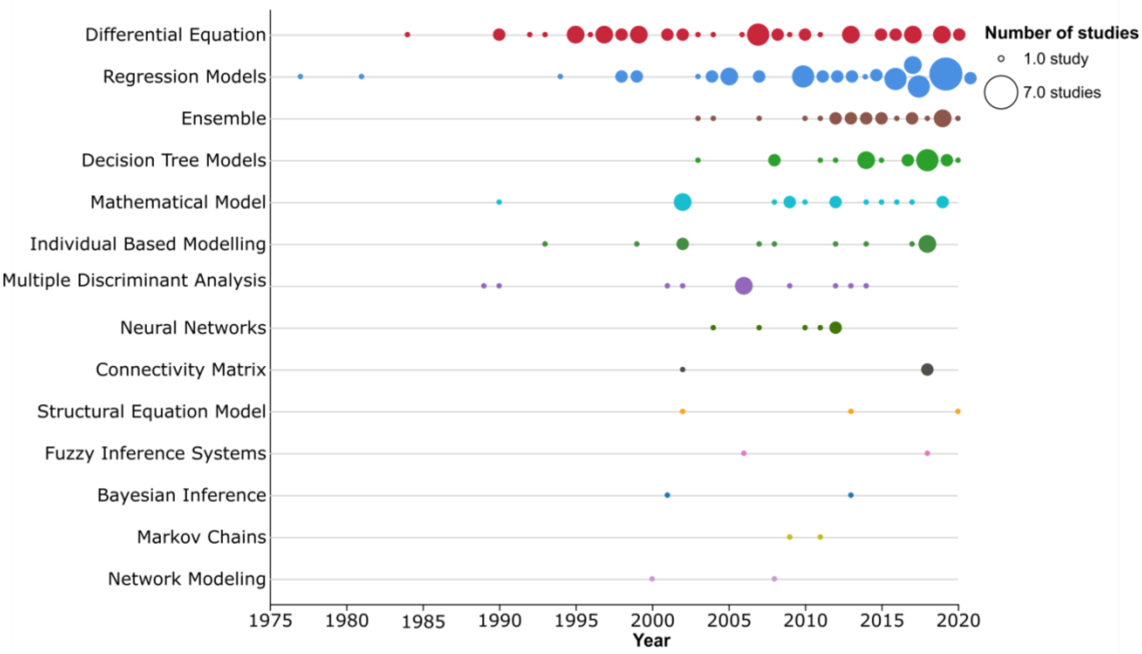

Fig 4 Main Methods used for modeling benthic fauna over the four decades. Here are shown the methods applied in more than one study (freq. > 1)

In the third phase (2000-2009), 54 studies were carried out mainly in freshwater (42.5%; n = 23) and marine (40.7%; n = 22), followed by seven studies (12.9%) in the brackish water environment. In two studies (3.7%), predictive models that can be applied to benthic organisms inhabiting any aquatic environment were used. The most used approaches for modeling were Bioassessment (31.5%; n = 17), Species Distribution Modeling (16.7%; n = 9), Trophic Web Models (16.7%; n = 9), Population Dynamics (14.8%; n = 8), Ecological Function studies (9.3%; n = 5), Secondary Production (5.6%; n = 3) and Dispersion-Colonization (3.7%; n = 2) (**Fig 3**). The most used methods were Differential Equation (25.9%; n = 14), Regression Models (14.8%; n = 6), Multiple Discriminant Analysis (11.1%; n = 6), Mathematical Model (11.1%; n = 6), Individual Based Modelling (7.4%; n = 4), Decision Tree Models (5.6%; n = 3), Ensemble models (5.6%; n = 3) and Neural Networks (3.7%; n = 2) (**Fig 4**). During this phase 28 software were used, among which the most recurrent were R-Software (7.4%; n = 4), Ecopath (7.4%; n = 4), MatLab (5.5%; n = 3), SAS (5.5%; n = 3), RIVPACS (5.5%; n = 3), FORTRAN (3.7%; n = 2), Stella (3.7%; n = 2) and S-Plus (3.7%; n = 2). In eleven studies (20.4%) the software was not indicated (**Fig 5**).

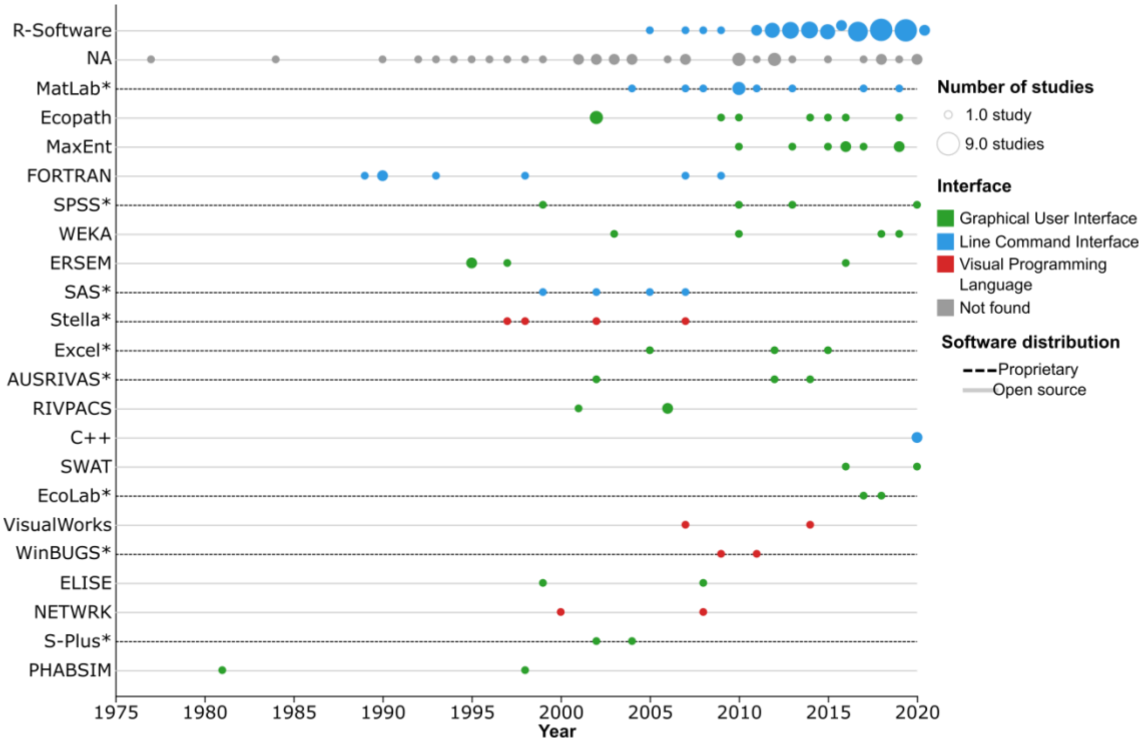

Fig 5 Main software (freq. > 1) used for modeling benthic fauna over the four decades. Colors indicate interface types and lines indicate if distribution is open source (free distribution) or proprietary

In the fourth phase (2010-2020), 122 studies were retrieved which were carried out mainly in marine (43.4%; n = 53) and freshwater (40.2%; n = 49) environments, followed by 12 studies (15.6%) in the brackish water environment. In one study (0.8%), a predictive model was proposed to a generic aquatic environment. The most used approaches for modeling were Species Distribution Modeling (45.1%; n = 55), Bioassessment (22.1%; n = 27), Dispersion-Colonization (11.5%; n = 14), Trophic Web Models (8.2%; n = 10), Secondary Production (5.7%; n = 7), Ecotoxicological (4.9%; n = 6) and Population Dynamics (2.5%; n = 3) (**Fig 3**). The most used method were Regression Models (27%; n = 33), Ensemble (14.8%; n = 18), Differential Equation (14.8%; n = 18), Decision Tree Models (12.3%; n = 15), Mathematical Model (7.4%; n = 9), Individual Based Modelling (4.9%; n = 4), Neural Networks (3.3%; n = 4), Structural Equation Model (2.5; n = 3), Multiple Discriminant Analysis (2.5%; n = 3), Fuzzy Inference System (1.6%; 2) and Connectivity Matrix (1.6%; 2) (**Fig 4**). During this phase 36 software were used, among which the most recurrent were R-Software (39.4%; n = 48), MaxEnt (6.5%; n = 8), MatLab (5.7%; n = 7), Ecopath (4%; n = 5), WEKA (2.5%; n = 3) and SPSS (2.5%; n = 3). In fourteen studies (11.4%) the software was not indicated (**Fig 5**).

Additionally, in relation to software characteristics, such as license type (i.e., free or proprietary) and user interface, among the 22 most popular software, 13 were based on Graphical User Interface (GUI) while software using Command Line and Visual Programming Language (VPL) are represented by five and four software, respectively. Finally, researchers preferred to use Open Source (n = 13) over Proprietary (n = 9) license software (**Fig 5**).

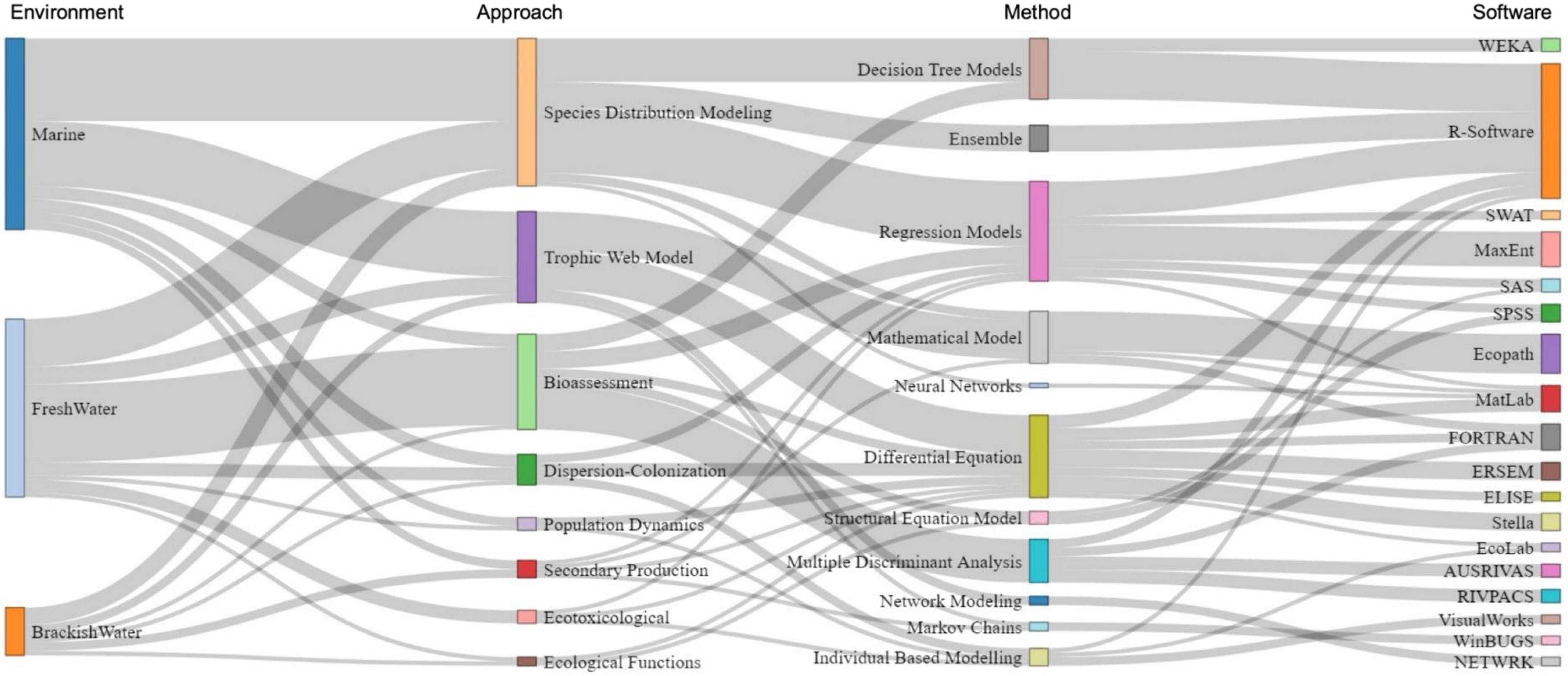

Fig 6 Alluvial diagram indicating the relationship between variables (columns) used to perform predictive ecological modeling of benthic fauna (i.e., Environment, Approach, Method and Software). In this network, blocks represent clusters of nodes (papers) belonging to the same category and edges represent the connection between these clusters from different variables. The size of the block represents the size of the group and the edge width indicates the number of components connected by each edge

Overall, there was little difference in the number of studies carried out in the marine (43%) and freshwater (41%) environments (**Fig 6**). However, only 16% of the studies were carried out in estuaries. Most studies in the marine and estuarine environment used Species Distribution Modeling and Trophic Web Model as the main modeling strategy while in the freshwater environment most studies focused mainly on Bioassessment and, secondarily Species Distribution Modeling. Studies based on Species Distribution Modeling mostly used Regression Models (e.g., logistic regression), Decision Tree Models (e.g., Random Forest) and Ensemble models. Bioassessment studies mainly used Multiple Discriminant Analysis, Decision Tree Models and Regression Models. Finally, Trophic Web Model studies used methods based on Mathematical Model and Differential Equation as simulation strategies. Among the most popular software R, Ecopath, MaxEnt, MatLab and FORTRAN were the most used and are associated with the most used methods such as Regression Models and Differential Equation (**Fig 6**).

Discussion

Evolution of approaches in different environments

Macrobenthic predictive modeling as a research topic has received contributions from studies carried out mainly in marine and freshwater environments and, to a lesser extent, in brackish water environments. In the early years, there was a distinction regarding the objectives of the studies. Studies in freshwater focused on the development of models that used biota as a tool to predict the impacts caused by changing environmental variables (e.g., acidification and water flow) (Gore and Judy Jr., 1981; Weatherley and Ormerod, 1989). Thus, they used the benthic organisms responses as a way to access and predict the environment status (Stalnaker et al., 1995). In marine and brackish water environments, the main objectives were related to testing ecological theories (e.g., simulations of factors that influence patterns of diversity, carrying capacity and organisms interactions) (Hughes, 1984; Levinton and Lopez, 1977; Platt and Lambshead, 1985).

From the 1990s onwards, several approaches showed an increase in the number of studies. The first increase was registered for studies that dealt with the energy flow between trophic levels (Trophic Web Models).

Trophic Web Model studies carried out in the marine environment investigated, for example, carbon cycling (Rowe, 1998; Ruardij and Van Raaphorst, 1995), fish species top-down control over the benthic community (Pockberger et al., 2014) and, more recently, themes associated with emerging topics such as recovery of benthic communities to high carbon dioxide exposure (Lessin et al., 2016). In the freshwater environment, Trophic Web Models addressed issues such as pollutants bioaccumulation and biomagnification (Morrison et al., 1996; Patwa et al., 2007), top-down population control (Descy et al., 2003; Hong et al., 2020) and invasive species impact on trophic relationships (Paillex et al., 2017; Zhang et al., 2019). In the estuarine environment, studies focused on themes such as eutrophication (Le Pape et al., 1999), macrofauna influence on debris cycling (Alemanno et al., 2017) and aquaculture impact on the benthic community (Sequeira et al., 2008). The Trophic Web Models had more impact on the research topic between 1995 and 2002 and maintained a constant production.

Bioassessment studies became more frequent after the 2000s and had a greater contribution from the freshwater environment. In this environment, there where increased interest in predicting the impacts of land use (e.g., agriculture, urbanization) (Lee et al., 2020) combined with the climate change effects (Guse et al., 2015; Li et al., 2018). In the marine environment were recurrent studies on the impacts of the aquaculture on benthic fauna (Jusup et al., 2007; Weise et al., 2009), eco-social impacts of the non-native species introduction (Ortiz and Stotz, 2007), regional climate change effects such as North Atlantic Oscillation (Junker et al., 2012) and glaciers melting (Torre et al., 2017). In the estuarine environment, the most recent studies have focused mainly on predicting biological parameters (e.g., composition, abundance, richness) of the benthic fauna (Rosa-Filho et al., 2004), estuarine sections classification using community structure (Marchini and Marchini, 2006) and disturbance quantification (e.g., eutrophication) in the estuarine system (Miller et al., 2018). Interest in bioassessment studies has shown the greatest growth since 2005 and is on the rise.

Species Distribution Modeling was the approach that showed the most recent growth and had the highest number of publications. Although this type of approach is mostly used in the marine environment, the first studies were carried out in the freshwater environment (Gore et al., 1998), where emerging machine learning techniques (e.g., Neural Networks, Decision Tree Models) were applied to predict species occurrence (D’heygere et al., 2003; Dedecker et al., 2004). The greatest growth was observed from 2010 where this approach was used mainly in the marine environment to simulate habitat suitability (Peterson and Herkül, 2019; Reiss et al., 2011). In addition, this approach was associated with emerging themes that contribute to the creation of management support tools (e.g., priority conservation areas)(Gonzalez-Mirelis and Buhl-Mortensen, 2015; Rioja-Nieto et al., 2013), climate change large-scale impacts on the benthic fauna distribution (Weinert et al., 2016) and invasive species expansion monitoring (Crickenberger, 2016). In the freshwater environment, in addition to the habitat suitability models creation (Hoang et al., 2010; Jowett and Davey, 2007; Li et al., 2009), more recently, the SDM's addressed issues such as distribution shifts due climate change effects (Domisch et al., 2013) and small-scale modeling of the species distribution (Kuemmerlen et al., 2014; Mehler et al., 2017). The development of small-scale species distribution models is critical to support management as it is more aligned with the ecosystems scale (e.g., bays, rivers, lakes and estuaries)(Becker et al., 2020; Singer et al., 2016). Finally, the studies in brackish water environment focused on the fauna distribution influenced by the environmental gradients (e.g., salinity, sediment and nutrients) (Bucas et al., 2013; Gogina and Zettler, 2010; Šiaulys and Bučas, 2012). Species Distribution Modeling is an approach in recent rise and showed promise for assessing environmental change at different scales and dealing with emerging issues such as climate change and invasive species.

Evolution of the methods

Classical modeling methods such as Differential Equations and Regression Models were most frequently used. Models based on Differential Equation were used mainly in population dynamics studies (Savina and Ménesguen, 2008; Torre et al., 2017), larval dispersion (Lal et al., 2020; Yearsley and Sigwart, 2011), invertebrate drift (Anderson et al., 2017), trophic relationships (Descy et al., 2003) and nutrient cycling (Rowe, 1998; Ruardij and Van Raaphorst, 1995). Regression Models were more associated with themes such effects of human interventions in the aquatic environment (e.g., artificial cascades) and climate change effects on species distribution (Gore et al., 1998; Moraitis et al., 2019), secondary production (Tumbiolo and Downing, 1994) and bioassessment studies (Dowd et al., 2014). In addition to the classic methods, emerging methods such as Decision Tree Models, Individual Based Models, Neural Networks and Structural Equation Model were also among the most frequent. Decision Tree Models were more associated with Species Distribution Models studies (Gezie et al., 2020). Individual Based Models were more applied to Population Dynamics studies (Alexandrids et al., 2017) and Dispersion-Colonization (Conklin et al., 2018). From the 2000s onwards, the Ensemble method was recurrently used. This method consists of combining the results of different modeling techniques (e.g., Random Forest, Maximum entropy) to obtain better predictive performance (Elith et al., 2008; Reiss et al., 2015).

On the other hand, there are methods allow combining different approaches to answer more complex questions. For instance, Individual Based Models are able to integrate information from the life cycle (e.g., spatial dispersion and growth) of each individual to functional relationships with the ecosystem and biological interactions (e.g., predation and competition) to generate predictive β-diversity models (Alexandridis et al., 2018). Thus, emerging methods are being successfully employed in approaches that are already well explored and also have contributed to the incorporation of new levels of complexity into models, allowing the investigation of processes through the understanding of mechanisms acting at different scales.

Main software used to model benthic fauna

In general, the most used software has shown greater growth since the 2000s. Most of them have an interface based in CLI (Command Line Interface), (e.g., R, Matlab, Fortran, SAS and C ++). CLI-based programs are faster and more flexible than those developed in other types of interfaces (e.g., Graphical User Interface and Visual Programming Language). Flexibility means which the user can edit pre-existing script codes (also called 'routines', 'libraries' or 'packages') and create their own scripts to suit their needs (Chen and Zhang, 2007). Among the most popular software the most used was R which is a freely distributed programming language created in 2003 and which is based on a command line interface (R Development Core Team, 2016). Although this last feature seems to be an impediment for non-programmers, the number of publications in various areas of science citing R is on the rise, especially in biological sciences (Tippmann, 2015). The first record was in 2005 with the Species Distribution Modeling in the freshwater environment (Sanderson et al., 2005). Its popularity grew from 2010 onwards, being applied in practically all approaches, mainly to Species Distribution Modeling. The versatility of R and its ability to rapidly incorporate emerging techniques (e.g., machine learning) (Nunes et al., 2020; Tippmann, 2015) may be important features for the future growth of benthic fauna modeling as a research topic (Petrovskii and Petrovskaya, 2012; Pickett et al., 2013). A very likely trend is that R will become the main tool within this research topic. For instance, popular GUI programs were incorporated into the R environment (e.g., Maxent, Ecopath) (Lucey et al., 2020; Phillips, 2017). Additionally, packages were created to 'translate' files from popular software based on VPL (e.g., Stella®) (Naimi and Voinov, 2012) and GUI (e.g., OpenBugs) (Sturtz et al., 2010) for the R environment allowing researchers working on different platforms to collaborate.

Software based on Graphical User Interface was more diverse and its popularity is due to its familiar and intuitive interface to most users. It is important to highlight the importance of software developed by government agencies and institutional partnerships. For instance, the PHABSIM (Physical Habitat Simulation) software developed by the USGS (U.S. Geological Survey) government agency uses statistical models (e.g., Exponential Polynomial Analysis and GAM) to explore the relationships between environmental variables and benthic fauna in Bioassessment studies. (Gore and Judy Jr., 1981; Hayes et al., 2015). The success of this initiative allowed the development of other software such as RIVPACS (River Invertebrate Prediction and Classification System) and AUSRIVAS (Australian River Assessment System) that incorporated new techniques (i.e., Multiple Discriminant Analysis) to the Bioassessment approach. In this way, it was possible to address new issues such as eutrophication (Nichols et al., 2014) and dams impacts on benthic fauna (Marchant and Hehir, 2002). Similarly, in the marine environment, predictive tools were developed through institutional partnerships such as Ecopath software (NOAA, 2017) and ERSEM (European Regional Seas Ecosystem Model) (Baretta et al., 1995) applied as ecosystem models through the Trophic Web Model approach. These tools were used to establish reference conditions (Davy-Bowker et al., 2006) and setting goals for conservation (Duarte et al., 2020; Welp, 2001). Thus, it is highly recommended that government agencies encourage institutional partnerships in the development of such tools aiming at management goals. As pointed out by Carvalho et al., (2015) the choice of software can be linked to its availability. We identified that software designed to address specific approaches can be an important factor in consolidating an approach within the research topic. Additionally, software based on emerging machine learning techniques such as Decision Tree Model (e.g., WEKA) and Fuzzy Inference Systems (e.g., CASiMiR) have been used to solve old and new research questions such as abundance prediction (D'heygere et al., 2003), habitat suitability (Gezie et al., 2020; Hough et al., 2019) and use of macroinvertebrates as indicators of pathogenic microorganisms (Jerves-Cobo et al., 2018).

Software based on Visual Programming Language (e.g., Stella, Visual Works) were less recurrent. Model building using this interface is based on 'drag and drop' graphic elements (e.g., boxes, wires) and linking them by arrows (Myers, 1990). Studies using this type of interface were used to solve issues involving the structure and evolution of processes (e.g., Population Dynamics, Secondary Production) (Rowe et al., 1997; Van Den Brink et al., 2007). This is perhaps the most intuitive and attractive form of modeling for non-programmers who can build a simulation starting directly from the conceptual model(Costanza and Voinov, 2001). Thus, it represents an important tool for teaching modeling. Its limitation lies in the limited capacity to expand the models and process a very large amount of information (Jørgensen and Bendoriccihio, 2011; Naimi and Voinov, 2012).

Although modeling studies are carried out in different environments, the sharing of strategies and tools is an indication of the existence of a community of practice around the research topic (Wenger-Trayner, 1998). Thus, benthic fauna modelers can benefit from new approaches introduced by their colleagues working in different environments. The increasing incorporation of approaches and tools to expand the scope of questions that can be answered are an indication that the predictive modeling of benthic organisms is a research topic that tends to continue its growth. Finally, the availability of monitoring data is a growing movement, advances in the research topic can be reached in exploring this data using the latest methods (e.g., big data and deep learning) (Nunes et al., 2020).

Conclusion

Predictive benthic macroinvertebrates modeling is a research topic that began about forty years ago. The first studies were carried out independently in different ecosystems in the marine, estuarine and freshwater environments. Initially in the freshwater environment the benthic fauna was used to develop models to predict the ecosystem status, while in the marine and estuarine environment the models were used to create predictive models to test theoretical assumptions of ecology. During the early years there was an important inter-institutional effort to create modeling tools (e.g., RIVPACS, ERSEM, and Ecopath). More recently, due to computational advances that allowed the incorporation of new strategies, emerging themes (e.g., climate change and invasive species) were recurrently addressed in all ecosystems using similar strategies. For example, the last two decades have seen the growth of approaches such as Species Distribution Modeling, which has been shown to be important for assessing the effects of climate change. Among the most used software, R has become the most popular and due to its versatility and, as a free tool, it should continue to increase its importance for the research topic. Compared to marine and freshwater environments, the estuarine ecosystem has received less attention. The growing demand from managers for predictive responses related to the climate change effects makes it urgent to develop studies that consider such effects at a local scale. In this sense, small-scale species distribution modeling studies can be carried out to assist decision-makers in ecosystem management.

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Capítulo 2

Trends of sea-level rise effects on estuaries: A qualitative and quantitative synthesis towards for a simple general model to estimate future saline intrusion in estuaries

Manuscrito a ser submetido ao periódico ***Marine Environmental Research***

Trends of sea-level rise effects on estuaries: A qualitative and quantitative synthesis towards for a simple general model to estimate future saline intrusion in estuaries

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Abstract

The Sea-Level Rise (SLR) already has effects on estuarine ecosystems around the globe. In this study, we used the systematic review to perform a qualitative and quantitative synthesis of predictive studies that investigated the effects of sea-level rise on estuaries. The results showed that most studies were carried out in the northern hemisphere and investigated the effects of saline intrusion through numerical hydrodynamic modeling. Ecological studies used a predictive approach and laboratory experiments and mainly dealt with the flooding and salinity increase effects. The quantitative synthesis showed that the relationship between saline intrusion and SLR is direct and inverse in relation to river flow. The incorporation of hydrodynamic models to ecological models and simulations that assess the effects of human interventions to mitigate the sea-level rise impacts on estuaries are recommended. Such information can be decisive for decision-makers to propose strategies for adapting to the sea level rise effects.

Keywords: Saline Intrusion, Climate Change; Coastal Management; Ecological Impacts; Mangroves

1 Introduction

One of the effects associated with climate change is the sea-level rise (SLR), which is particularly worrying since 80% of the world population lives in the coastal zone (Nicholls, 1995) and approximately 10% of the population lives in coastal areas with elevations below 10 meters. Such low elevation coastal zones, including many bays and estuaries, are particularly vulnerable to flooding (McGranahan et al., 2007) which have the potential to generate large losses to due to the close relationship between human activities (e.g., fishing and aquaculture) and such ecosystems (Huppert et al., 2003; Mclusky and Elliott, 2008).

The Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) projected that the global sea level may increase up to 60 cm by 2100 due to warming ocean waters and melting glaciers (Stocker et al., 2013). However, the accelerated reduction in polar masses (Allison et al., 2009; Velicogna, 2009) increases the possibility of future SLR of 1 m or more (Pfeffer et al., 2008). Global SLR values still vary widely in forecasts ranging from 30 to 180 cm by 2100 (Stocker et al., 2013) but regional-scale studies projections suggested that it can reach up to 2 m (Kuang et al., 2014; Nicholls et al., 2011; Sriver et al., 2012). Paradoxically, the potential effects of SLR on estuarine ecosystems are by and large poorly understood (Robins et al., 2016).

The speed at which the average sea level rises is increasing (Watson et al., 2015). For instance, evidences from tide gauge surveys indicated that sea levels have increased at a rate of 1.7 ± 0.3 mm / year since 1950 (Church and White, 2011). Although, since the 1990s sea level rise has been measured by high-precision satellite altimetry and between 1993 and 2009 it was observed that the rate at which the average sea level increased may reach 3.3 ± 0.4 mm/year (Ablain et al., 2009). The accelerated rates of sea level rise demand studies that assess the short-, medium- and long-term impacts in transition environments in coastal zones.

The results of satellite altimetry revealed that sea level rise is not uniform (Carson et al., 2016), furthermore, in some regions (e.g., Western Pacific) sea level rise occurs three times faster than the global average (Nicholls, 2011). These variations are partially explained by the non-uniform regional distribution of heat and salt in the ocean (Wunsch et al., 2007) and by isostatic movements (i.e., due to tectonic activity) which also change the relative sea level (Christie-Blick et al., 1988). This raises the need to understand how different sea-level rise magnitudes affect transitional environments around the globe.

Non-climatic components of sea-level variation associated with anthropogenic activities (e.g., oil extraction, groundwater and dams) can also amplify the local vulnerability (Nicholls, 2011). For instance, the dams building can intensify saline intrusion by reducing the fresh water input into estuaries (Alcérreca-Huerta et al., 2019; Le et al., 2007). On the other hand, reductions of sediment supply in river deltas by dam construction throughout the 20th century may cause land uplift counterposing sea level by about -0.5 mm/year (Chao et al., 2008). Although extremely important for creating appropriate mitigation strategies, these non-climatic components of SLR receive less attention than the climatic components because they are considered a local issue (Nicholls and Cazenave, 2010).

The physical impacts of sea-level rise are well known (Nicholls et al., 2007), short and medium-term effects are submergence (Little et al., 2017a; Temmerman et al., 2013), increased flooding in coastal lands and saline intrusion in estuaries (Eidam et al., 2020; Robins et al., 2016). In the long-term, processes such as erosion will reshape the coastal zone and saline intrusion will affect groundwater reservoirs (Nicholls et al., 2007; Reeve and Karunarathna, 2009). Ecological effects such as mangroves and salt marshes retraction due to reduced sediment supply, are also expected in future likely impacting important ecosystem services as carbon storage (Perera et al., 2018). All of these processes (e.g., salinization, flooding) may generate direct and indirect socio-economic impacts and the prediction is that the magnitude of the impacts will become increasingly apparent (Nicholls et al., 2007). For instance, the coast of the African continent, and south, southeast and east Asia are identified as endangered regions due to the high population living in delta regions (Nicholls and Cazenave, 2010). Unfortunately, there is a lack of the effects of SLR of the other regions of globe since, for instance southern hemisphere estuaries are not included in the search for general ecological models (Barros et al., 2012). Therefore, it is expected that the studies already carried out will provide relevant information on how these systems are responding and what are the projections for future scenarios (Robins et al., 2016).

The lack of available information on local sea-level rise is clearly impeditive for management and decision making (Thorne et al., 2017). In contrast to sea-level rise studies on a global scale, predictive studies that assess the sea-level rise impacts on regional and local scale (e.g., estuaries) are more diffuse in the literature. In this sense, a synthesis will help to improve our understanding of the effects of sea level rise on saline intrusion in estuaries, if there are general trends predicted by models. Thus, the objective of this study is to perform a qualitative and quantitative synthesis of the expected impacts of sea-level in estuarine systems.

2 Methods

2.1 Systematic review

The review process followed the PRISMA protocol for systematic review (Moher et al., 2009). The search was performed on the *Web of Science* platform in December 2020 using the search string: ((sea level rise OR SLR OR climate chang*) AND (estuar* OR river*) AND (saltwater intrusion OR salinity intrusion OR salt-hedge OR sal*)). After a few rounds of search it was identified that the term related to saline intrusion showed variations that reduced the number of retrieved target articles. Thus, the synonyms were added to the search string. The search period was from 1945 to 2020. After obtaining the search result, the files were downloaded and eligibility criteria were applied.

2.1.1 Screening criteria

After records search, documents were read to select the articles that addressed the prediction of sea-level rise effects in estuarine systems. The included studies accessed topics in which SLR has a direct impact (e.g., saline intrusion, flooding and estuarine erosion process) for future SLR scenarios, ecological impacts due to SLR or changes in environmental conditions (e.g., increased salinity) and evaluation of interventions to mitigate the effects of the SLR. The excluded articles dealt with processes in the estuary were not related to sea-level rise. For instance, studies that measured or simulated saline intrusion or erosion and silting in the estuary due to factors such as natural reduction of discharge or artificial (e.g., construction of dams), floods associated with events (e.g., monsoons) and ecological impacts not associated with sea level rise (e.g., cover loss and introduction of invasive species) were excluded. After applying the eligibility criteria, the articles were read to extract the relevant information for our study.

2.1.2 Records retrieved in the systematic review

A total of 81 records (i.e., papers) were retrieved from the *Web of Science* platform database, no duplicate articles were identified. After reading the titles and abstracts and applied the screening criteria, 15 documents that presented simulations of saline intrusion without the sea level rise influence were excluded, and 66 were kept. After reading the texts and applying the eligibility criteria, 5 records were deleted and 61 kept. Among the excluded, three were review studies and two dealt with saline intrusion due to the operation of dams. For the qualitative analysis, 61 papers were included, among which 26 contained information that was extracted for quantitative analysis (**Figure 1**).

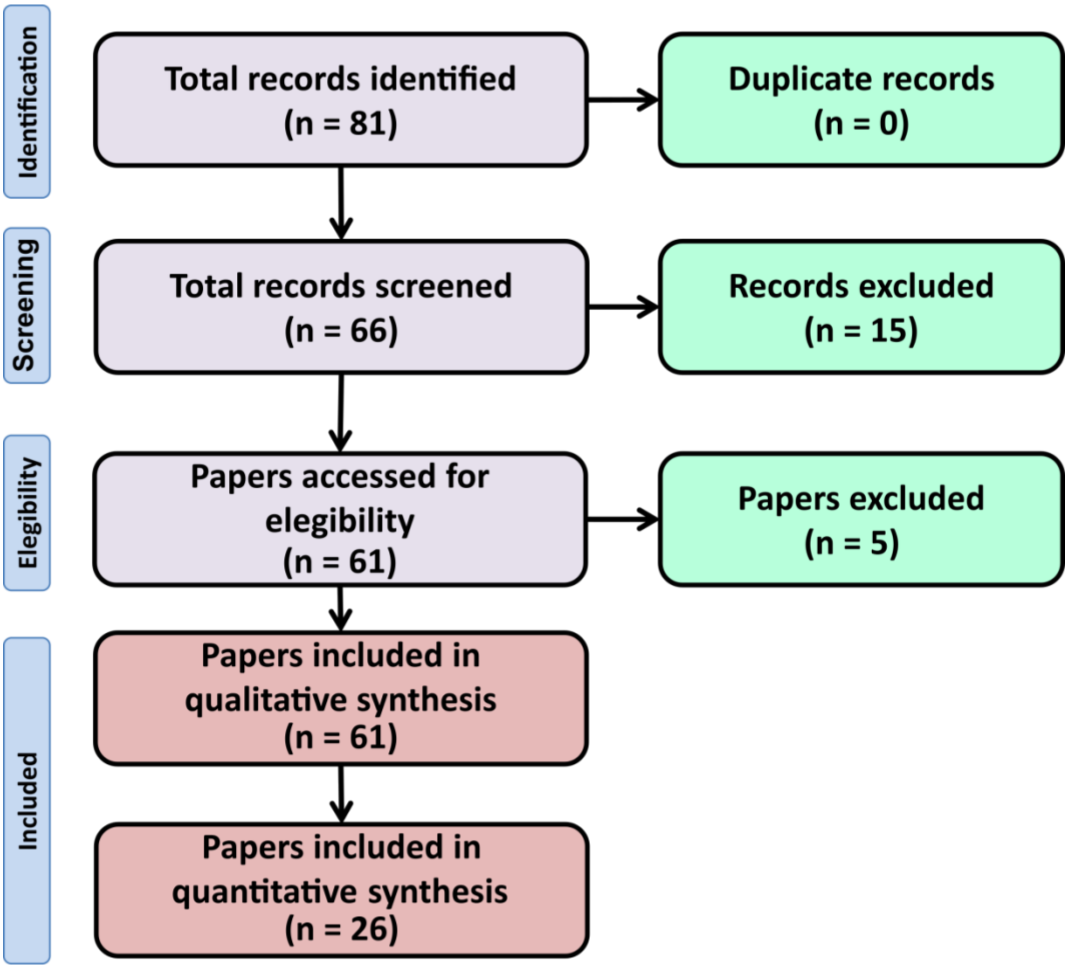

Figure 1. PRISMA diagram indicating the number of records retrieved in the search, articles evaluated for eligibility and documents included in this review after applying screening criteria.

2.2 Variables extracted from articles

The qualitative variables extracted from articles were related to manuscript identification (i.e., year of publication, title and authors), estuary (i.e., estuary name, country) and study category. The studies were classified into five categories based on the impacts caused by sea level rise on physical and biological variables and simulation of interventions in order to mitigate the sea-level rise effects (**Table 1**). All of this information was compiled into an electronic spreadsheet (Costa et al., 2022).

Table 1. General categories of the sea-level rise effects in estuaries

Study category	Description
Salinity intrusion	Studies that presented predictions about the effects of sea-level rise on saline intrusion in estuaries.
Ecological effects	Studies that dealt with potential SLR effects (e.g., saline intrusion, flood) on the biota.
Sedimentary dynamic	SLR effects on sediment erosion, transport and deposition.
Management Tools	Studies that presented management strategies for mitigation.
Water temperature	SLR effects on estuary temperature.

In addition to the qualitative variables, four quantitative variables whenever available were extracted from the articles, these were: (i) the extension of the estuary based on the maximum salinity penetration in the baseline scenario (present); (ii) the position of isohalines in the baseline scenario and in different scenarios of sea-level rise and (iii) the isohalines position on different scenarios of river discharge.

2.3 Data extraction

The position of the saline wedge was extracted in different scenarios (e.g., sea-level rise and discharge) using the WebPlotDigitizer software (Rohatgi, 2012). The extracted values were used to calculate the saline intrusion increment in different sea-level rise scenarios and to investigate the discharge influence on saline intrusion.

2.4 Data treatment

The saline intrusion was calculated through the difference between saline wedge length in the baseline scenario ($s_{present}$) and future scenarios (s_{future}) (**Figure 2**). These values were measured from the same spatial point downstream to its maximum extent towards the upstream.

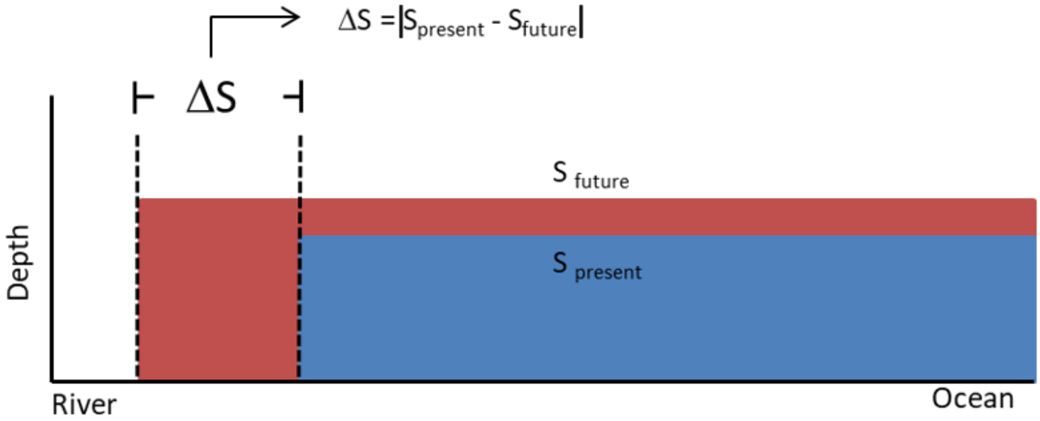

Figure 2. Saline intrusion length calculation obtained by difference between the present ($S_{present}$) and future (S_{future}) saline wedge length.

However, the saline intrusion is influenced by the estuary length. In order to make the values comparable, the Saline intrusion increment ($S_{increment}$) was estimated by dividing the saline intrusion by the present saline wedge length (**Equation 1**).

$$s_{increment} = \frac{(|s_{present} - s_{future}|)}{s_{present}} \qquad (1)$$

2.5 Statistical analysis

In order to investigate the relationship between sea-level rise and the saline intrusion increment and the influence of discharge on the magnitude of this effect, a linear multiple regression analysis was used. The predictor variables were SLR (m) and discharge (m^3s^{-1}) and the response variable was the saline intrusion increment (dimensionless). The linear multiple regression was performed using '*lm*' function in the software R (R Development Core Team, 2016). From the multiple regression model, future scenario predictions were made for a real estuary considering SLR scenarios (0.25, 0.5, 0.75 and 1) and characteristic discharge for the Jaguaripe estuary (Q = 363 m^3s^{-1}) (SNIRH, 2019).

3 Results

3.1 Evolution of publications

Over nearly thirty years (1992 to 2020), there was an increase in the number of publications related to the sea-level rise effects on estuaries (**Figure 3**). The first study retrieved in the search was carried out in 1992 and was unique for a decade. In the following decade (between 2000 and 2010) there was a gradual increase in the studies frequency but a marked growth occurred in the last ten years (2010-2020).

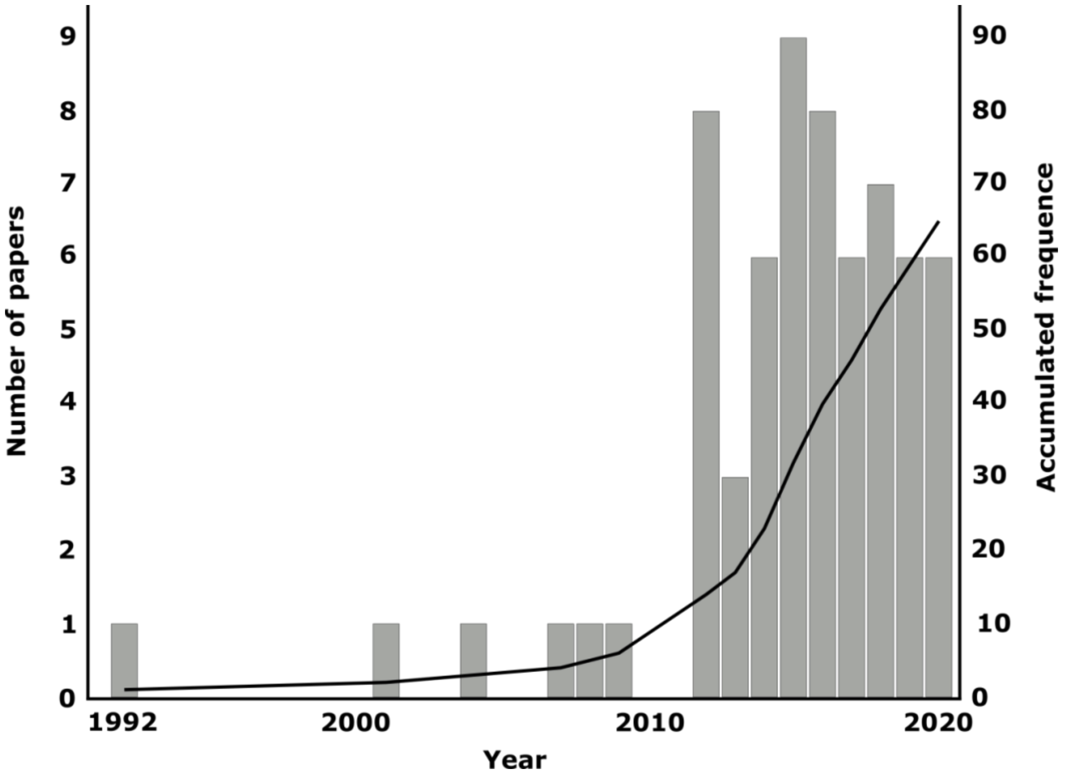

Figure 3. Trend of publications related to the Sea-level rise effects on estuaries.

3.2 Global distribution of studies on the sea-level rise effects in estuaries

Studies on the sea-level rise impacts in the estuaries were carried out mainly in the northern hemisphere (**Figure 4**). The main countries that performed such studies were the USA and China. The most frequent objectives were to investigate the sea-level rise effects on (i) salinity intrusion in the estuary, (ii) ecological effects on estuarine fauna and flora, (iii) transport of suspended sediment, erosion, deposition and changes in estuarine geomorphology (iv) management tools formulation and (v) heat distribution pattern on estuary (**Figure 4**).

Most studies that sought to investigate the sea-level rise effects on saline intrusion were performed using hydrodynamic numerical models (blue in **Figure 4**), statistical models (red), machine learning (light green) and digital terrain elevation models (pink). Predictions of how sea-level rise would affect erosion, transport and sediment deposition, as well as changes in estuarine geomorphology (i.e., squares in **Figure 4**) were carried out using hydrodynamic models, statistical models and systems dynamics modeling.

Ecological predictions (i.e., triangles in **Figure 4**) were made using digital elevation models, statistical models, hydrodynamic modeling and laboratory experiments. In a particular case, sea level rise was used as the background for a study (i.e., hypothetical scenario) that aimed to predict the fish genetic adaptation to environmental change due to saline intrusion. In addition, there were studies that aimed to create management tools related to investigating estuary sensitivity, potential economic and social impacts and assessing the managers preparedness in face of saline intrusion due to sea-level rise scenarios. The management tools created to address such issues were based on results from hydrodynamic models, digital elevation models, systems dynamics models and expert assessment based on publications for the region analyzed.

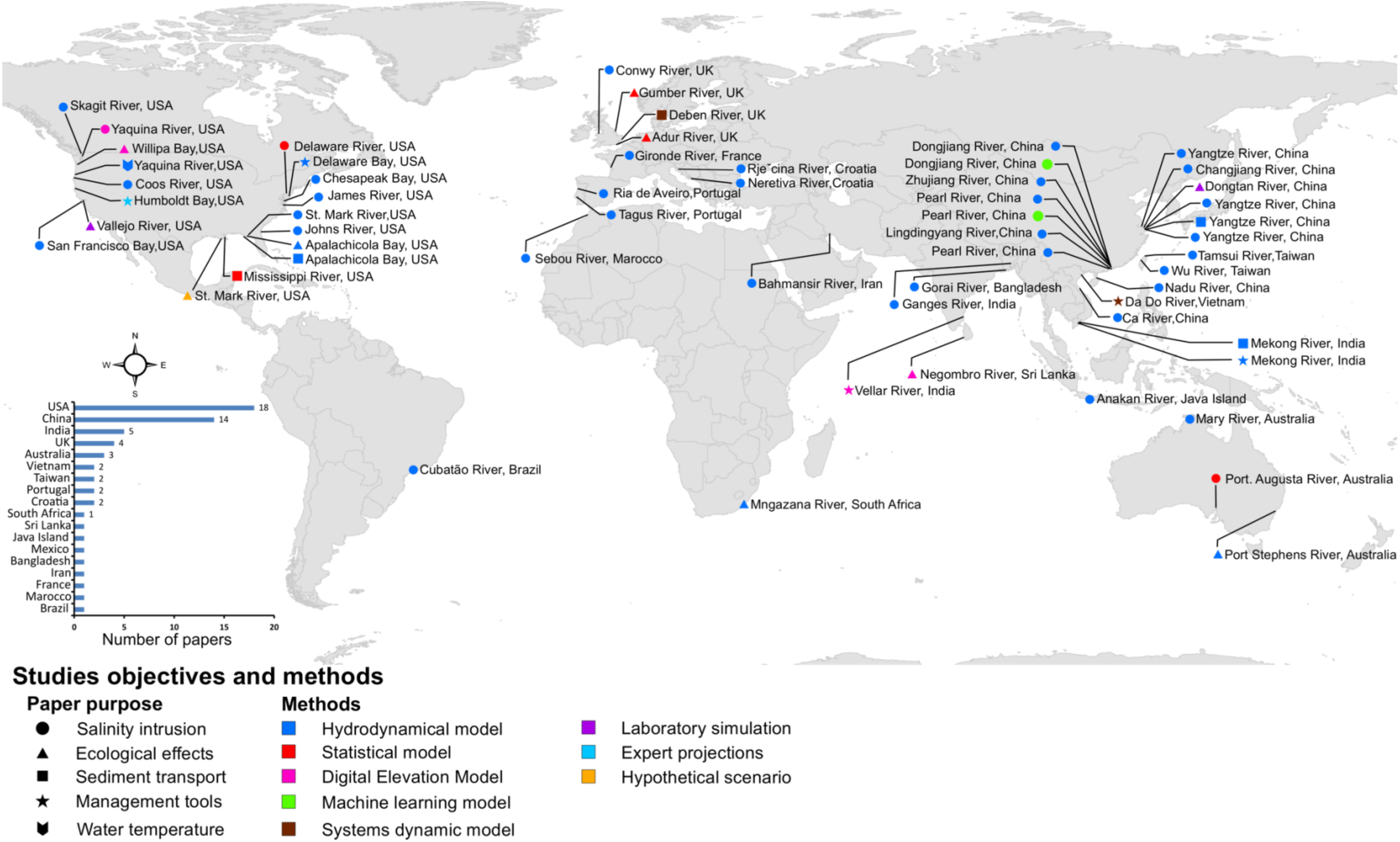

Figure 4. Worldwide distribution of the studies on the sea-level rise effects on estuaries. Different symbols refer to studies objectives and colors represent different methods used at each study.

3.3 Qualitative synthesis

3.3.1 Ecosystems simulation models

All the hydrodynamic numerical modeling were calibrated and validated in each study. Some simulations were carried out in idealized estuaries and later applied to real estuaries (e.g., Chua and Xu, 2014; Krvavica and Ružić, 2020). Techniques were combined to improve the simulation results. For instance, hydrodynamic models were coupled with process-based modeling to assess salt transport (Rodrigues et al., 2019) and statistical modeling (using Monte-Carlo method) to improve the prediction for estuarine systems with few data (He et al., 2018). The studies that applied machine learning methods used past databases (e.g., salinity, discharge, tide, winds) to make future predictions for saline intrusion (Lin et al., 2019).

3.3.2 Scenarios

The scenarios chosen were based mostly on climate change projections made by the IPCC (Intergovernmental Panel for Climate Change) (Stocker et al., 2013), government agencies (e.g., NOAA) and on specific research of the studied system (e.g., Rice et al., 2012). The studies considered sea-level rise scenarios combined with increasing the amplitude of hydrological events (e.g., periods of prolonged drought inducing a discharge reduction), subsidence (W. Chen et al., 2020), storms and cyclones (Akter et al., 2019) and future interventions (e.g., dredging) (Eidam et al., 2020).

3.3.3 Sea-Level Rise effects on estuaries

Considering the predicted future scenarios, in general, studies suggest that saline intrusion is highly sensitive to sea-level rise (Yuan et al., 2015). In addition to the increase in the estuarine salinity, the sea-level rise may also increase the estuarine water residence time (Chen et al., 2015), tide range upstream (Hong et al., 2020), stratification (Y. Chen et al., 2016) and tidal prism volume (Krvavica and Ružić, 2020).

According to most simulations, the region of the lower estuary (Euhaline zone) will be the most influenced by the sea-level rise effects (Xiao et al., 2014; Zhou et al., 2017), mainly in shallow estuaries (mean depth < 10 m) (Krvavica and Ružić, 2020). However, in some simulations, it was found that the sea-level rise has a greater effect in intermediate than at the lower and upper estuary (e.g., W. B. Chen et al., 2015; He et al., 2018). Particularly, in flow reduction scenarios, the greatest effects can be seen in the upper estuary portion (Oligohaline zone), with salinities increasing from the intermediate region to upstream (Rice et al., 2012).

3.3.4 Discharge effects on saline intrusion increment

Most studies pointed to river discharge as the main factor influencing salt intrusion forced by sea level rise in estuaries (Robins et al., 2014). Under higher flow conditions, the river discharge acts to reduce the effect of saline intrusion (Zhou et al., 2017). However, the greatest sea-level rise influence occurred in discharge reduction scenarios where there was a greater saline intrusion (Akter et al., 2019). Therefore, most studies have shown that saline intrusion is directly related to sea level rise and inversely related to river discharge (Etemad-Shahidi et al., 2015; Haddout and Maslouhi, 2018; Liu and Liu, 2014). In addition to the discharge, studies pointed to stratification as an important factor that influences saline intrusion in the estuary. While in shallow and well-mixed estuaries the spread saline intrusion is more efficient (Vargas et al., 2017) in estuaries with strong stratification, the spread of the salinity intrusion is reduced even in low flow conditions (Y. Chen et al., 2016; Khangaonkar et al., 2016).

3.3.5 SLR impacts on human activities

The main sea-level rise effects on estuaries are associated with the floods represented by the increase in the tidal prism (Krvavica and Ružić, 2020) and the increase in saline intrusion upstream. The recovered records focused mainly on saline intrusion and its impacts on water for consumption and agriculture. The results show that in moderate scenarios of sea-level rise (i.e., 2030), minor impacts are expected (Tri and Tuyet, 2016). However for scenarios predicted for 2100 it is expected that the "*salinity violation*" values (how many times the salinity exceeds the drinking water salinity of 0.45 psu) may exceed between 45 and 48% the reference value in high latitudes (Etemad-Shahidi et al., 2015; Haddout and Maslouhi, 2018).

3.3.6 Intervention

Considering the impacts caused by saline intrusion on human activities, simulations were carried out to assess the efficiency of interventions (e.g., dams). The results showed that although the dam prevents saline intrusion from affecting the drinking water reservoirs upstream of the dam, a reduction of up to 25% in productivity in the downstream region is expected (Hariati et al., 2019). Similarly, simulations of the construction of submerged barriers (i.e., weirs) to reduce flow velocity also proved ineffective for moderate scenarios and can aggravate flood events contributing to the creation of hypersaline plains (Miloshis and Valentine, 2013).

3.3.7 SLR effects on sediment and heat distribution pattern

In addition to the effect on salinity and flooding, there were studies that have predicted how the sea-level rise effects can affect other processes (e.g., erosion and transport and sediment deposition) and distribution of variables (e.g., temperature) in the estuary. Hydrodynamic simulations showed that for sediment transport more moderate scenarios did not show changes in relation to the baseline scenario and for more extreme scenarios (e.g., 2100) the intensification of erosion and deposition processes become too complex to be estimated (Ngoc et al., 2013). Hydrodynamic simulations were also used to predict geomorphological alteration processes at the mouth of the estuary due to the sediment supply reduction (Luan et al., 2017) and suspended (Huang et al., 2016).

The potential losses in areas caused by flooding associated with sea-level rise were simulated with potential losses for mangroves, agriculture and aquaculture (Saleem Khan et al., 2012) and that in the medium term built structures increase the flow and sandbanks erosion and in the long term they intensify the siltation process in the estuary (Le et al., 2007).

3.3.8 Ecological impacts

The ecological impacts of sea-level rise were predicted for plants (e.g., seagrass and mangroves), benthic fauna and fish. The effect of flooding can result in a loss of up to 64% in seagrass coverage (Shaughnessy et al., 2012). The combined effect of flooding and saline intrusion can result in up to 46% in biomass reduction

(Woo and Takekawa, 2012), facilitate the establishment of invasive seagrasses (Xue et al., 2018), lead to changes in the spatial distribution of species (Davis et al., 2016), cover loss (Yang et al., 2014) and reduction in the process of carbon storage by mangrove forests (Perera et al., 2018).

For the benthic fauna, the main sea-level rise effect studied was the saline intrusion in the estuary. The effect of increasing salinity can affect oyster growth (Huang et al., 2015). The saline intrusion on estuaries can affect on the distribution and composition of the community (Little et al., 2017b). Furthermore, the combined effect of flooding with artificial structures (e.g., walls) along the estuary (i.e., coastal squeeze) can result in a reduction of up to 23% of the benthic macrofauna total biomass in wetlands (Fujii and Raffaelli, 2008).

3.4 Quantitative synthesis

3.4.1 Description of estuaries studied

The studied estuaries varied in size between 4 and 320 km, considering the distance from the estuary mouth to the maximum penetration of the zero isohaline. The sea-level rise amplitude scenarios ranged from 0.05 m to 2 m. The shortest estuary (Skagit River Estuary, USA) simulated a sea-level rise scenario of 0.46 m and obtained a maximum saline penetration of 420 m for isohaline of 0.5 (Khangaonkar et al., 2016). The longest estuary (Chesapeake Bay, USA) presented the lowest saline intrusion value (around 3 km for 0.5 isohaline) in the scenario of 0.4 m of sea-level rise and 11 km for the scenario of 1 m of sea-level rise (Hong and Shen, 2012).

3.4.2 SLR effects on salinity intrusion length

In general, a positive relationship was observed between sea-level rise and the increase in saline intrusion (**Figure 5**). In this graph, points represent the salinity intrusion increment values in the different sea-level rise scenarios while the colors correspond to the simulated discharge scenario. For the studies analyzed, the sea-level rise increased the value of saline intrusion increment. The values of saline intrusion increment showed high variability among the studies for the same values of sea-level rise (**Figure 5**). For instance, the 1 m rise in SLR resulted in a saline intrusion increment that ranged from 4% (Hong and Shen, 2012) to 331% (Krvavica and Ružić, 2020).

Since the salinity along an estuary is affected by river discharge, numerical modeling studies considered this variable in the simulations. The discharge values varied between 0.62 m³/s (minimum discharge scenario) (Krvavica et al., 2017) and 28300 m³/s (maximum discharge) (W. Chen et al., 2016). The saline intrusion increment was inversely related to discharge. This means that for the same sea-level rise scenario, higher discharge values will result in lower saline intrusion values (**Figure 5**). Additionally, from the multiple regression model, it was possible to infer that for scenarios of sea-level rise below 0.25 m and flows close to 30000 m³/s it is possible that there is a decrease in the saline intrusion length in the estuary (**Figure 5**).

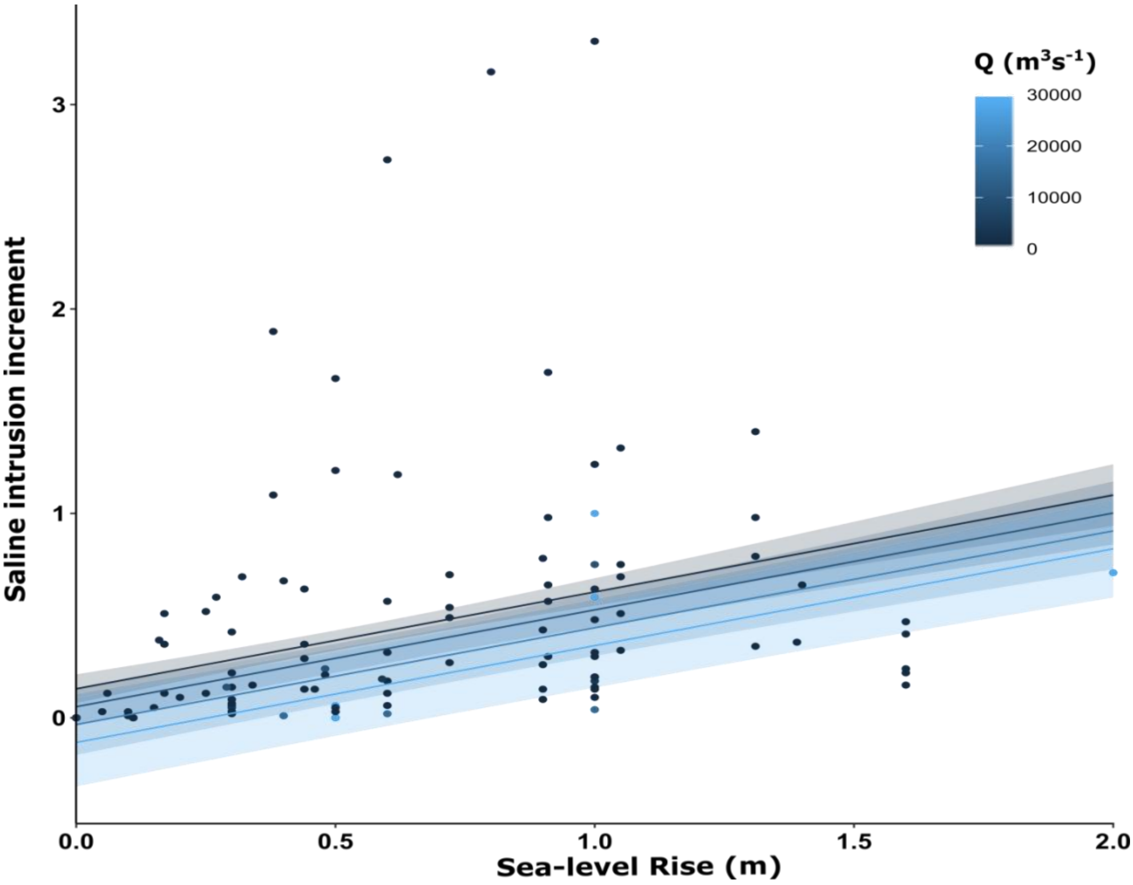

Figure 5. Saline intrusion increment in the different sea-level rise scenarios extracted from the 26 articles obtained in the systematic review. Each point in this multiple regression represents the 0.5 isohaline in different discharge scenarios. The different lines and dots color represent the different discharge Q (m^3s^{-1}) magnitude from the estuaries. Grey lines represent discharges close to zero and light blue represents discharges close to 30000 (m^3s^{-1}).

3.5 Estimating the saline intrusion increment from sea-level rise scenarios

From the multiple regression model, it is possible to predict new saline intrusion increment values based on SLR and discharge (**Figure 5**). We used these results is to estimate saline intrusion scenarios in Jaguaripe estuary. In this case study, saline intrusion values were predicted using the multiple regression model. SLR data and typical discharge from the Jaguaripe River were used (Q = 363 m^3s^{-1}) (SNIRH, 2019) (**Table 2**).

Table 2. Predicted saline intrusion estimators for the Jaguaripe estuary. The coefficients were obtained from the expected values for SLR and estuary typical discharge (**Figure 6**).

	Prediction	CI (Confidence interval)		Prediction Interval (PI)	
SLR	Fitted	Lower	Upper	Lower	Upper
0.25	0.26	0.15	0.37	-0.79	1.31
0.50	0.38	0.28	0.47	-0.67	1.43
0.75	0.49	0.39	0.60	-0.56	1.54
1.0	0.61	0.48	0.74	-0.44	1.67
2.0	1.09	0.79	1.38	0.00	2.17

To obtain the saline intrusion increment values, we used the scenarios generated by the 'Fitted' predicted coefficients (moderate scenario) and the model prediction interval (extreme scenario) (**Figure 6**). Applying these values to the length of the saline wedge of the Jaguaripe estuary, expected salinity distributions were obtained for different SLR scenarios.

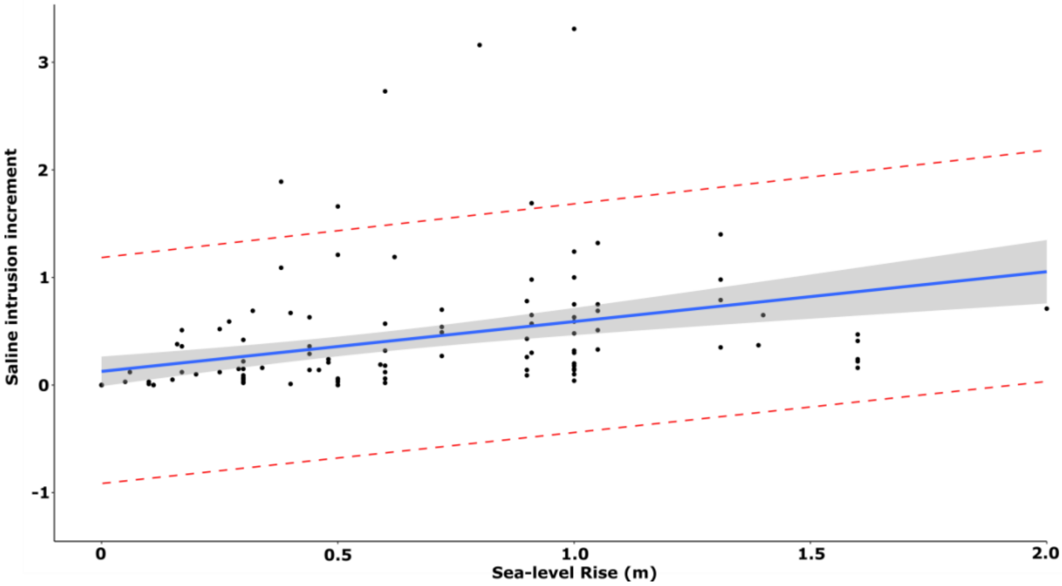

Figure 6. Saline intrusion increment in the different sea-level rise scenarios. The moderate saline intrusion increment scenarios were obtained to the sea-level rise values using mean model (blue line) and the extreme scenarios using the model prediction interval (red dotted line).

Comparing the salinity distribution along the estuary longitudinal section for the present (**Figure 7A-B**) with the scenarios predicted from the multiple regression model (**Figure 7C-H**), the minimum salinity scenario can reach about 13 km upstream in addition to the value registered for the present scenario. While for maximum salinity this increase can reach 20 km.

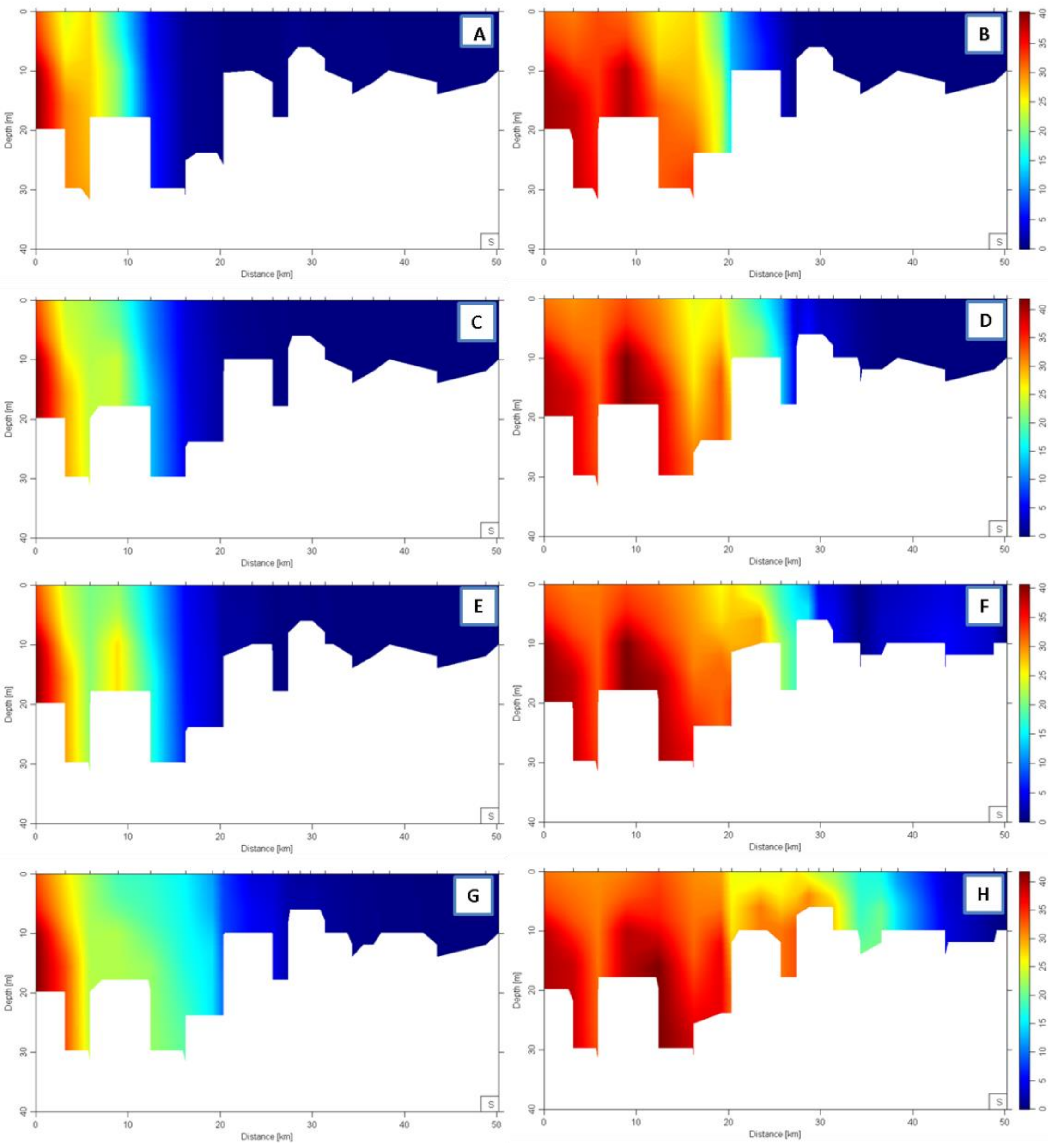

Figure 7. Salinity intrusion scenarios for Jaguaripe River estuary. Minimum salinity values (left) and maximum (right). The represented scenarios were present (A-B), 0.50 m moderate (C-D), 1 m moderate (E-F) and 1 m extreme (G-H).

4 Discussion

Predicting the sea-level rise effects on estuaries is a research topic that has emerged over the past 30 years. Studies have become more frequent since the 2000s and had greater growth since 2012. The increase in the number of studies from this period onwards is associated with the introduction and improvement of satellite altimetry (Watson et al., 2015). The resolution and accuracy increased allowing investigations of sea-level rise at regional and local scales (Carson et al., 2016). Particularly for management, this is a key information, since the scarcity of local scale accurate data is pointed out as a limiting factor in decision making (Thorne et al., 2017).

4.1 Worldwide distribution of the studies on the sea-level rise effects on estuaries

Most of the studies were on the eastern and western portion of the North American continent, the western coast of the European continent, and the south and southeast of the Asian continent. The regions of South and Southeast Asia coincide with areas indicated as most vulnerable to the sea-level rise effects and subsidence processes (Nicholls and Cazenave, 2010). Possibly, the largest number of studies in these regions may have been motivated by the already noticeable effects of the increase in sea level near densely populated regions (Nicholls, 2011, 1995; Slangen et al., 2014). The small number of studies carried out in the southern hemisphere represents a gap in knowledge and raises the need for further studies to assess its vulnerability, especially in regions that present sea level rise values above the global average (Carson et al., 2016).

The use of hydrodynamic numerical models has the advantage of providing a detailed spatial and temporal description of the dilution and transport processes of the variables (e.g., salt, sediment and suspended matter). The results provided by these models allow the use in other predictive models (e.g., ecological) (e.g., Savina and Ménesguen, 2008) and assist managers in decision making. However, the performance quality lies in the amount of observed data on salinity, hydrology, and estuary high-resolution topography, in addition to the significant effort for setting up, programming and computational resources (Lin et al., 2019). These factors may represent a limitation on the use of hydrodynamic modeling by managers to prepare for the sea level rise effects in estuaries, especially those further away from more developed areas due to resources and technical support limitations (Thorne et al., 2017). Recently, machine learning techniques have been applied to saline intrusion prediction in the estuary (Lin et al., 2019; Zhou et al., 2017). The combination of these techniques in the process of building such models is a promising way to deal with the scarcity of data (He et al., 2018).

The overall sea-levels rise effects on estuaries (e.g., coastal flooding, saline intrusion) are well known in global and regional scale (Robins et al., 2016). The results presented here show several tools for reaching more detailed forecasts of how sea-level rise may affects estuaries locally. The increase in the average sea level induces an increase in the tide range upstream (Hong et al., 2020), the estuary water volume (tidal prism) (Krvavica and Ružić, 2020), likely causing flooding and increases in water residence time and stratification (Chen et al., 2015; Y. Chen et al., 2016). However, the results of the combination of these processes at different estuaries are highly variable. For instance, sea-level rise can induce increase in stratification (Khangaonkar et al., 2016), which in turn can reduces saline intrusion (Y. Chen et al., 2016). The intensification of stratification may compromise oxygen exchanges between the upper and lower layers (Hong and Shen, 2012). This type of scenario can represent ecological risk for benthic and planktonic communities (Hallett et al., 2018). To deal with such issues, more complex models need to be created.

Studies have shown that the variability in prediction of saline intrusion due to sea level rise was strongly influenced by river discharge (Hallett et al., 2018; Ross et al., 2015). Our result shows the importance of considering other climate change effects on estuaries (e.g., drought scenarios), since the intensification of the saline intrusion process has great potential to cause economic and ecological losses (Shaughnessy et al., 2012; Shirazi et al., 2019).

Future scenarios suggest an intensification of extreme events, mainly severe droughts and temperature increase (IPCC) (Stocker et al., 2013). In these scenarios, the decrease in drainage is expected to influence the increase in salinity due to evaporation and saline intrusion in parts of the upper estuary, in addition to reducing the supply of sediment. This extreme salinity scenario poses a risk to human activities such as collect drinking water (Etemad-Shahidi et al., 2015), agriculture, aquaculture and industry (Rice et al., 2012; Yang et al., 2015). Simulations aiming at evaluating the sea-level rise mitigation intervention efficiency are scarce and presented mitigation results restricted to a portion of the estuary and in the short and medium-term (Miloshis and Valentine, 2013; Hariati et al., 2019). For instance, the use of check dams can prevent the salinization of water upstream, while in the lower part, discharge reduction can promote a marinization process (Hallett et al., 2018; Nunes-Vaz, 2012) that could impact activities, such as fishing (Alcérreca-Huerta et al., 2019; Prasad et al., 2018). Studies that estimate the ecological damage caused by mitigation interventions are also rare. For example, physical barriers to prevent flooding can lead to habitat and biomass loss of benthic species due to coastal squeeze (Fujii and Raffaelli, 2008) and saline intrusion can be enhanced by the discharge control by dams (Alcérreca-Huerta et al., 2019; Prasad et al., 2018) leading to estuarine marinization and favoring the exclusion of species less tolerant to higher salinity (Woo and Takekawa, 2012), being replaced by opportunistic species or even by invasive species (Xue et al., 2018). Thus, in addition to the physical effects, it is important that decision-makers consider the inclusion of models that estimate the potential ecological impacts associated with such interventions.

4.2 Quantitative synthesis

The quantitative analysis showed that even with great variability between the systems (e.g., size and discharges) the sea-level rise results in a saline intrusion increment on the estuary and this increment is strongly influenced by river discharge (Hallett et al., 2018; Robins et al., 2016). The result obtained in this quantitative synthesis (i.e., multiple regression model) represent the expected general trend for saline intrusion in estuaries and can be used to explore possible sea-level rise scenarios. This exploratory tool can have important implications for management. Since most coastal regions are experiencing the acceleration of sea-level rise rate (Willis and Church, 2012) and effects will be perceived differently across regions (Nicholls, 2011), managers should consider such effects when planning future mitigation measures. Thus, efforts must be made to predict the sea-level rise effects in different estuaries around the globe. Simultaneously, simulations to estimate potential impacts of mitigation interventions must be measured.

Since the construction of more complex models (e.g., hydrodynamic numerical models) takes time and resources, an application of the model obtained in this quantitative synthesis can be an initial exploration of plausible scenarios for future saline intrusion length increase. Here, saline intrusion scenarios were obtained for the Jaguaripe estuary and should be considered as a preliminary step to estimate saline intrusion since it is sensitive to several factors such as geomorphology, depth and local hydrodynamics (Robins et al., 2016; Willis and Church, 2012).

Finally, the search for the synthesis of general patterns helps us to better understand the mechanisms that govern processes and allow us to draw forecasts for future events (Pickett et al., 2013; Underwood et al., 2000). Different studies carried out around the globe have shown a clear pattern of increased saline intrusion in response to sea-level rise. These studies also pointed out the important role that river discharge plays in regulating saline intrusion. Additionally, they showed that human interventions such as dams construction have a great potential to aggravate the saline intrusion effects such as hypersalinization, loss of species, biomass and favoring exotic species (Hallett et al., 2018). Such information is important for defining strategies on how managers should prepare for the impacts that will come in the medium and long term (IPCC, 2021; Thorne et al., 2017).

5 Conclusion

Over thirty years of sea-level rise effects research in estuaries, predictive models were developed to investigate its influence on salinity, flooding and sediment transport. The overall model presented here derived from climate change projections indicated that sea-level rise will result in saline intrusions. These studies showed saline intrusion magnitude is strongly influenced by the river discharge, mainly in decrease flow scenarios that increase the saline intrusion. Studies have also shown that changes in the salinity pattern of the estuary have economic (e.g., salinization of aquifers and soil) and ecological (e.g., biomass loss, species exclusion and favoring of exotic species) implications, affecting important services (e.g., carbon storage). Thus, the search for predictive tools that help to estimate such impacts at a local scale are particularly important for managing these ecosystems. In this sense, hydrodynamic models were the main predictive tool. Ecological studies that evaluated the effects of sea level rise in estuaries mainly used strategies such as measurement, laboratory manipulative studies and models based on geographic information systems. In this sense, we encourage the use of the hydrodynamic models results as a basis for forecasting future scenarios of the sea level rise effects (e.g., saline intrusion and flooding) in ecological studies since the predictions generated by the hydrodynamic models are more accurate and properly adjust to the scale of the estuaries. Future efforts should be made to build modeling tools that can present satisfactory results with less data (e.g., incorporation of machine learning techniques into systemic models) and to create decision support tools to assist managers in sea-level rise predictive models use (e.g., data collection, model conception and results interpretation). Increasing the reliability of sea-level rise data forecasts on a regional scale coupled with the improvement of predictive modeling techniques allow scientists to work to generate better quality data to meet the complex demand of decision-makers in face of this problem so challenging that is our adaptation to climate change.

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Capítulo 3

Sea-level rise effects on macrozoobenthos distribution within an estuarine gradient using Species Distribution Modeling

Manuscrito submetido ao periódico ***Ecological Informatics***

Sea-level rise effects on macrozoobenthos distribution within an estuarine gradient using Species Distribution Modeling

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Abstract

The sea-level rise induced by Climate has caused impacts (eg floods and saline intrusion) in estuaries. In this work, we used monitoring data (salinity, sediment and taxa occurrence), simulated saline intrusion and Species Distribution Model to predict the spatial distribution of families in the estuary at two levels of SLR (0.5 m and 1 m) for two scenarios (moderate and extreme). For the simulation, we used the ensemble method applied to five models (MARS, GLM, GAM, RF and BRT). High AUC and TSS values indicated "good" to "excellent" accuracy. RF and GLM obtained the best and worst values, respectively. The model predicted local extinctions and new colonization in the upper estuarine zones. With the effects of climate change intensifying, it is extremely important that managers consider the use of predictive tools to anticipate the impacts of climate change on a local scale on species migration.

Keywords: Ecological predictive modeling; Ensemble Forecast; Machine-learning; Climate change; Random Forest

1 INTRODUCTION

We are living in a time of climate emergency (Nicholls et al., 2011; Slangen et al., 2014). The sixth Intergovernmental Panel for Climate Change report (IPCC, 2021) points out that the aggravation of various phenomena influenced by global warming such as droughts, floods and sea-level rise (SLR) (Hallegatte et al., 2013; Nicholls and Cazenave, 2010; Robins et al., 2016) is accelerating due to human action (Nerem et al., 2018). Furthermore, the results indicate, with very high confidence, that many of these processes such as ocean acidification and glacier melts are already irreversible (IPCC, 2021). As a result of the warming of the surface of the oceans and the melting of glaciers, we have been recording an acceleration in SLR (Church and White, 2011; Dangendorf et al., 2019; Velicogna, 2009; Watson et al., 2015). The SLR will affect human societies on a global and local scale (Nicholls et al., 2011), causing displacement of human communities living in the coastal area and enhancing coastal erosion influenced by marine transgression (Zhou et al., 2013). At smaller scales, in bays and estuaries, gradual loss of the coastline and saline intrusion is expected, likely causing drastic change in adjacent aquatic systems (e.g., rivers, lakes and groundwater) (Eidam et al., 2020; Phan et al., 2018). The salinization of these environments can result in economic (e.g., water catchment) and ecological losses (e.g., habitat reduction, introduction of exotic species and local extinction) (Davis et al., 2016; Little et al., 2017; Xue et al., 2018). Species displacement and biomass loss are also worrisome effects of rising sea levels in estuaries (Fujii and Raffaelli, 2008). Since transitional environments such as estuaries are among the first ecosystems to suffer from the sea-level rise effects (Carson et al., 2016), predictions of the potential impacts expected for these environments are extremely valuable for management and decision making (Thorne et al., 2017).

Estuaries are, by definition, characterized by having a salinity gradient formed by the dilution of oceanic water by river water (Pritchard, 1967) which is strongly influenced by precipitation and tides (Prandle and Lane, 2015). In addition, estuaries are subject to other gradients, such as sedimentary gradients, influenced by river and marine transport and organic matter in the water column and sediments (Compton et al., 2013; Glover et al., 2019; Peterson et al., 1984). The existence of such gradients requires organisms to develop evolutionary (e.g., low salinity and low oxygen) and behavioral (e.g., burrowing) adaptations to inhabit the estuarine environment (Elliott and Whitfield, 2011; Pearson and Rosenberg, 1978; Telesh et al., 2013a). Changes in salinity and sediment dynamics have the potential to cause significant impacts on the estuarine ecosystem (Wolansky and McLusky, 2012). For instance, the implementation of dams often reduces river discharge, favoring saline intrusion (Alcérreca-Huerta et al., 2019; Prasad et al., 2018) which can lead to an imbalance in the ecosystem (e.g., opportunistic species bloom) (Schone et al., 2003). Similarly, sea-level rise has the potential to change salinity patterns in ecosystems in the medium term (i.e., 2050) (Mohammed and Scholz, 2018; Robins et al., 2016). Several simulations of sea-level rise at a local scale using numerical models have shown that estuaries are suscetible to SLR effects, especially to saline intrusion (Prandle and Lane, 2015; Robins et al., 2016; Serrano et al., 2020). Changes in the salinity pattern can affect the structure (i.e., distribution, abundance and richness) of the benthic fauna (Kimmerer, 2002; Little et al., 2017). While the effects of sea level rise on salinity is a well-studied issue and general patterns are being elucidated (Little et al., 2017; Robins et al., 2016; Ross et al., 2015), other important variables for benthic macroinvertebrates such as sediment still have high uncertainty (Mulligan et al., 2019).

Numerical simulations of SLR influence on estuarine sediments transport suggest that for moderate scenarios (i.e., 30 cm in 2050) there is no expected change in the distribution of sediments, while for extreme scenarios (i.e., 100 cm in 2100) there is still great uncertainty about such changes due to the complexity of erosion and deposition processes (Mulligan et al., 2019; Ngoc et al., 2013).

The benthic fauna presents predictable responses to changes in environmental variables such as salinity and sediments (Anderson, 2008; Attrill, 2002), which in turn allows them to be used in monitoring and environmental impact assessment studies (Borja & Basset, 2012; Reiss et al., 2015). Thus, benthic fauna has a great potential to provide future responses of estuarine ecosystems to climate change effects, especially sea-level rise (Elliott et al., 2015; Gogina et al., 2010; Singer et al., 2016). Usually, changes in the species spatial distribution due to environmental changes (e.g., climate change) are recurrently addressed through Species Distribution Modeling (SDM's) (Guisan and Zimmermann, 2000). This approach uses species occurrence and environmental variables data to define the suitability of other areas where species may inhabit (Elith and Leathwick, 2009). Among the various applications are ecosystem management (Patrizzi and Dobrovolski, 2018), improving the sampling design of monitoring programs, assessing the risk of potential invasions of non-native species and forecasting future scenarios (Reiss et al., 2015). In general, species distribution modeling studies have focused on global and regional scale simulations (Degraer et al., 2008; Moritz et al., 2013; Weinert et al., 2016). At the local scale (i.e., less than 1 km²), species distribution projections are scarce (e.g., Becker et al., 2020; Mehler et al., 2017; Singer et al., 2016) due to the available climate change predictions being more compatible with the regional (1 km² to 10 km²) and global (>10^8 km²) scales (Guisan et al., 2007; Tyberghein et al., 2012). Predictions of SLR patterns at local scale are important to assess changes in the salinity distribution pattern at a scale compatible with the phenomenon (i.e., benthic distribution) (Becker et al., 2020). Understanding how changes caused by SLR affect the species distribution in estuaries is extremely useful for predicting how species relationships and ecosystem functioning will be affected by saline intrusion (e.g., Gogina et al., 2021). The aim of this work was to simulate the effects of sea-level rise on benthic macroinvertebrates distribution along the estuarine environmental gradient using Species Distribution Modeling and a set of environmental layers refined to the local scale.

2 Methods

2.1 Study area and data

The Jaguaripe River estuary is a shallow estuary (the average depth is less than 10 m) dominated by tides, and represents one of the main tributaries of the Todos os Santos Bay. It has a surface area of 2200 km² and a mean monthly discharge of 28 m^3s^{-1} (Cirano and Lessa, 2007). The sediment spatial distribution pattern is characterized by the predominance of sandy sediments, with the coarse sand fraction upstream with a reduction of these sediment fractions towards the downstream where the predominant fractions are medium to fine sand. The salinity in the Jaguaripe estuary is characterized by the formation of a gradient from downstream (marine environment) that reaches a maximum salinity of 41 to upstream (freshwater environment) where salinity reaches zero (Barros et al., 2008). The marked distribution of salinity allows classification into salinity zones as proposed by the Venice system (Venice System, 1959). This classification defines estuary zones based on the salinity in the Euhalina (30-40), Polyhaline (18-30), Mesohaline (5-18) and Oligohaline (0.5-5) zones. This type of classification can be a useful tool to study the salinity influence on the distribution of organisms (Bleich et al., 2011; Wolf et al., 2009). The upstream region is dominated by polychaetes of the Nereididae, Capitelidae and Spionidae families. In the intermediate regions, the bivalve Tellinidae is dominant, and further downstream, greater richness is observed and taxa such as polychaetes of the Cirratulidae, Sillydae, Maldanidae and Sternaspidae families are quite frequent (Barros et al., 2012). These taxa play important roles in the ecosystem (e.g., nutrient cycling, aeration of lower sediment layers, fragmentation of organic matter)(Martins and Barros, 2022).

All benthic macrofauna samples were collected along the estuarine longitudinal gradient between 2006 and 2019 in 8 field campaigns (for more details about methods see **Appendix A**). The sites for biological and environmental (i.e., sediment and salinity) sampling were collected over 13 years (2006, 2007, 2009, 2010, 2014, 2016, 2019a and 2019b) along the long-term monitoring program of the Todos os Santos Bay estuaries (biological data available in Barros et al., (2021)). For the 2006, 2007, 2009, 2014, 2016 and 2019a campaigns, the design consisted of collecting macrofauna samples in 10 sampling stations (n = 8 replicates per station; total = 80 per campaign) using a 'corer' sampler (cylinder 10x15 cm) (**Figure 1**). Additionally, sediment samples were collected and surface salinity measured with a refractometer, data logger (HOBO$^{©}$) and multiparameter probe (Horiba$^{©}$) in 10 georeferenced sampling stations distributed along the longitudinal section of the estuary. In the collections carried out in 2010 (n = 65 samples) and 2016 (n = 21 samples) the samples were collected using the same method at sampling points along the cross section of the estuary in different zones of the estuary (i.e., euhaline, polyhaline, mesohaline and oligohaline) (**Figure 8**). Finally, in the 2019b campaign, biological samples were collected (total = 120 samples) randomly distributed in the different zones of the estuary (n = 10 per zone; n = 3 replicates per point) (**Figure 1**) using a van veen grab sampler.

2.2 Occurrence data

Data from 254 benthic sampling sites were used as an input for distribution models. The taxa used in the simulation were the most representative. To obtain the most representative taxa, a table was created containing the results of all sampling campaign and select the most recurrent taxa with the highest abundance values (>70% of the total abundance) along campaigns.

The taxonomic resolution was standardized for the family since a considerable part of the campaigns used this classification. The chosen families were Cirratulidae, Magelonidae, Nereididae, Orbiniidae, Spionidae, Tellinidae, Pilargidae and Paraonidae. According to evidence, this decision should not significantly influence the results since studies in which taxa multivariate responses are tested, show that the use of family resolution introduces less noise into the analysis than the species resolution level (Bailey et al., 2001; Souza and Barros, 2014).

2.3 Environmental data

Salinity and sediment data were used as independent variables in the models to predict the macrobenthos spatial distribution. This data obtained during the monitoring program were used to create a spatial data grid. The spatial data grids were converted to raster layers in a geographic information system (ESRI ArcGIS geodatabase file) by using the IDW (Inverse Distance Weighting) method. Since the macrobenthic fauna spatial distribution is strongly influenced by the sediment pattern, which in estuaries occurs in small-scale mosaics (Anderson, 2008; Gimínez et al., 2005; Ysebaert and Herman, 2002), the 10 m spatial resolution was defined for all environmental layers to be compatible with the fine-scale fauna distribution. The sediment classes used as environmental layers were pebble, granule, very coarse sand, coarse sand, medium sand, fine sand, very fine sand and mud (silt and clay fractions). This sediment data was used in present and future scenario models as it was assumed that sediment does not change significantly over time (Barros et al., 2012; Mulligan et al., 2019; Ngoc et al., 2013).

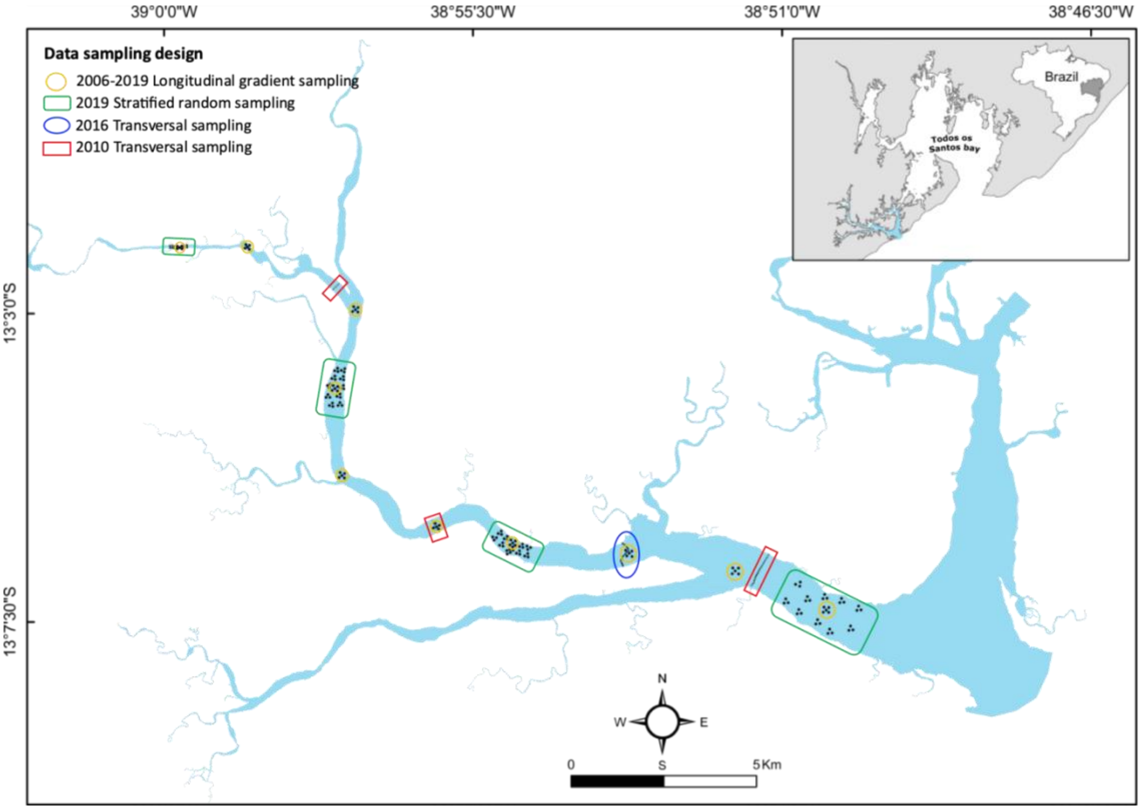

Figure 1. Sampling points from monitoring program in the Jaguaripe estuary. There were five campaigns carried out at 10 points and one campaign carried out in four regions along the estuarine longitudinal gradient and two campaigns carried out in four regions along the transverse gradient (i.e., between the margins).

2.4 Sea-Level Rise scenarios

Baseline scenarios (i.e., without sea-level rise influence) were created from the minimum and maximum salinity data obtained in the monitoring program. For this, the maximum and minimum values recorded during the monitoring program for each sampling point were used. The salinity was measured using multiparameter probes (Horiba©) and data loggers (HOBO U24©).

Plausible sea-level rise scenarios were proposed through the quantitative synthesis from a systematic review of numerical models that simulated saline intrusion as a result of sea level rise in estuaries (Costa and Barros, Unpublished results). The predict function in R software (R Development Core Team, 2016) was used in the GLM (i.e., multiple regression model) to obtain the saline intrusion values for each scenario. The calculation consisted in the product of saline increment value associated with Jaguaripe estuary discharge by the isohalines length. Minimum and maximum salinities were simulated for baseline and SLR scenarios (0.5 m and 1 m) under moderate (mean model) and extreme conditions (using model's prediction interval) (**Table 1**). To visualize the graphical representation of the scenarios, see **Appendix A** Figure A.2.

Table 1. Predicted saline intrusion estimators for the Jaguaripe estuary. The moderate scenario is represented by the fitted Prediction model and the extreme scenario by the upper Prediction Interval of the model.

	Prediction	CI (Confidence interval)		Prediction Interval (PI)	
SLR	Fitted	Lower	Upper	Lower	Upper
0.5	0.38	0.28	0.47	-0.67	1.43
1	0.61	0.48	0.74	-0.44	1.67

2.5 Species Niche modeling

2.5.1 Data preparation

The spatial autocorrelation between occurrence data was tested using SDMtoolbox package (Brown, 2014) on ArcGIS software (ESRI^{TM}) and autocorrelated occurrences were removed. The multicollinearity between the environmental variables was investigated using the occurrence data of each family by the method variance influence factor stepwised using the '*vifstep*' function of the *usdm* package (Naimi, 2017) do R (R Development Core Team, 2016).

2.5.2 Modelling techniques

Niche models were run for each taxon individually using the main techniques used to modeling macrozoobenthos distribution (Costa et al., Unpublished results). The modeling methods chosen were MARS (Multivariate Adaptive Regression Spline), GLM (Generalized Linear Models), GAM (Generalized Additive Models), RF (Random Forest) and BRT (Boosted Regression Trees). MARS is a non-parametric flexible regression modeling algorithm that uses hinge functions to fit models, through a recursive partitioning approach, where the number of parameters is automatically determinate by the data (Friedman, 1991). GLM is a linear model class that allows working with data that assume different types of distributions (e.g., normal, binomial and Poisson) and are fitted using link functions and the maximum likelihood principle (Nelder and Wedderburn, 1972). GAM are semi-parametric (i.e., exact parametric form of these functions is unknown) extensions of GLMs in which part of the linear predictor is specified in terms of a sum of smooth functions of predictor variables. GAM are useful for fitting non-linear relationships without prior assumptions on the shape of the response (Clark, 2013; Wood, 2006). Random Forest is an ensemble machine learning algorithm that uses input data (supervised learning) to create large number of independent decision trees (typically 500–1000) perform classification and regression tasks. The responses are predicted based on averages (regression) or by majority rules (classification) from all trees (Breiman, 2001). BRT is an ensemble method for fitting statistical models and combines the strengths of regression trees and boosting (an adaptive combination of simple models to obtain improved predictive performance). The final BRT model is an additive regression in which individual terms are simples trees, fitted in a forward, stage wise way (Reiss et al., 2015; Elith and Leathwick, 2009; Elith et al., 2008; Hastie and Tibshirani, 1990). For ecological applications and pros and cons see **Appendix B** (**Table B.1**) . Since the models results can present large discrepancies, the ensemble method was used to combine the results of the different models, incorporating their advantages and reducing the limitation of each technique (Thuiller et al., 2009). All models were fitted in R (R Development Core Team, 2016) version 4.1.0, using *sdm* package (Naimi and Araujo, 2016). The script and data used in the simulation is available in a Markdown format (Costa et al., 2022).

2.5.3 Evaluation of the predictive performance of models

Two metrics, the Area Under the receiver operating characteristic Curve (AUC) and True Skill Statistics (TSS) were used to assess the agreement between the presence-absence records and the predictions. The AUC metric measures the ability of a model to discriminate between sites where a species is present, versus those where it is absent (Hanley and McNeil, 1982). The AUC values range from 0 to 1, where a score of 1 indicates perfect discrimination, a score of 0.5 implies predictive discrimination that is no better than a random guess, and values <0.5 indicate bad predictions. According to Swets (1988), AUC values > 0.9 are considered highly accurate or “excellent”, between 0.7 - 0.9 moderately accurate or “good”, and those < 0.7 poorly accurate or “poor”. Since the evaluation based only on AUC is not highly informative and reliable (Raman et al., 2020), TSS scores were also estimated for accuracy (Allouche et al., 2006). TSS values larger than 0.8 are considered highly accurate (“excellent”), 0.8 to 0.6 substantially accurate (“Very good”), 0.6 to 0.4 moderately accurate (“Good”) and values less than 0.4 are considered “Poor” (Landis and Koch, 1977). Both metrics indicate that when we randomly take sites of presence and absence, it is expected that presence sites have higher suitability values in relation to absence sites (Elith et al., 2006). Finally, to evaluate the changes in the taxa distribution for the different scenarios in relation to the current scenario the '*niche.overlap*' function of the ENMeval package was used (Muscarella et al., 2018) in the R software (R Development Core Team, 2016).

3 Results

3.1 Models evaluation

The obtained ensemble models had AUC and TSS tests with good to excellent accuracy results (AUC average = 0.9; TSS average = 0.7) (**Figure 2A**). In general, the two metrics agreed in their results and the TSS was the more conservative metric and resulted in relatively lower values. For AUC, the models were classified as "Excellent" (n = 17), "Good" (n = 22), and one as "Poor". For TSS, 23 models were classified as "Very good", 9 as "Excellent", 5 as "Good" and 3 models were classified as "Poor" (**Figure 2B**). Both AUC and TSS had similar pattern and the methods that had the best performance were Random Forest, GAM, MARS and BRT, by decreasing order. While the GLM method showed the worst results. The least accurate model occurred for the Nereididae family when the GLM method was applied (**Table 2)**.

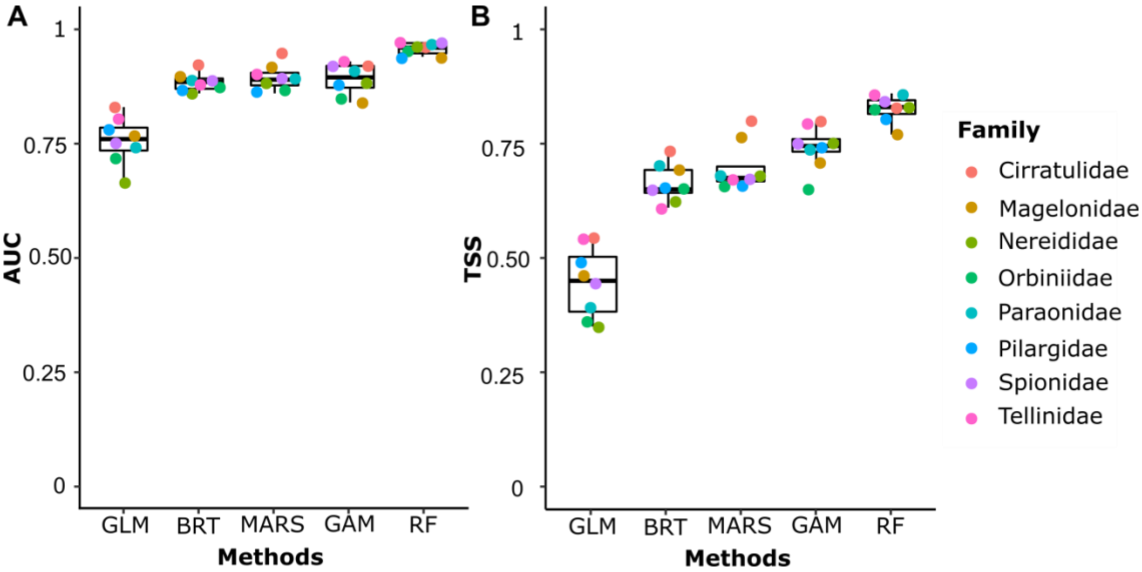

Figure 2. Performance of the five predictive modeling methods (Generalized Linear Models – GLM; Boosted Regression Trees – BRT; Multivariate adaptive regression spline – MARS; Generalized Additive Models - GAM and Random Forest - RF) for occurrence data based on AUC (A) and TSS (B) metrics. The performance of different methods is shown by a combination of strip charts and color dots indicating results for family.

Table 2. Performance of predictive model methods for ensemble final model using AUC and TSS. Excellent performances on both evaluators are highlighted in bold.

Occurrence points	Family	Method	AUC	AUC classification	TSS	TSS classification
91	**Cirratulidae**	**Random Forest**	**0.96**	**Excellent**	**0.83**	**Excellent**
	Cirratulidae	**GAM**	**0.92**	**Excellent**	**0.8**	**Excellent**
	Cirratulidae	**MARS**	**0.95**	**Excellent**	**0.8**	**Excellent**
	Cirratulidae	BRT	0.92	Excellent	0.73	Very good
	Cirratulidae	GLM	0.83	Good	0.54	Good
104	Magelonidae	Random Forest	0.94	Excellent	0.77	Very good
	Magelonidae	GAM	0.84	Good	0.71	Very good
	Magelonidae	MARS	0.92	Excellent	0.76	Very good
	Magelonidae	BRT	0.9	Excellent	0.69	Very good
	Magelonidae	GLM	0.77	Good	0.46	Good
133	**Nereididae**	**Random Forest**	**0.96**	**Excellent**	**0.83**	**Excellent**
	Nereididae	GAM	0.88	Good	0.75	Very good
	Nereididae	MARS	0.88	Good	0.68	Very good
	Nereididae	BRT	0.86	Good	0.62	Very good
	Nereididae	GLM	0.66	Poor	0.35	Poor
99	**Orbiniidae**	**Random Forest**	**0.95**	**Excellent**	**0.82**	**Excellent**
	Orbiniidae	GAM	0.85	Good	0.65	Very good
	Orbiniidae	MARS	0.87	Good	0.66	Very good
	Orbiniidae	BRT	0.87	Good	0.65	Very good
	Orbiniidae	GLM	0.72	Good	0.36	Poor
121	**Paraonidae**	**Random Forest**	**0.97**	**Excellent**	**0.86**	**Excellent**
	Paraonidae	GAM	0.91	Excellent	0.74	Very good
	Paraonidae	MARS	0.89	Good	0.68	Very good
	Paraonidae	BRT	0.89	Good	0.7	Very good
	Paraonidae	GLM	0.74	Good	0.39	Poor
115	**Pilargidae**	**Random Forest**	**0.94**	**Excellent**	**0.8**	**Excellent**
	Pilargidae	GAM	0.88	Good	0.74	Very good
	Pilargidae	MARS	0.86	Good	0.66	Very good
	Pilargidae	BRT	0.87	Good	0.65	Very good
	Pilargidae	GLM	0.85	Good	0.49	Good
130	**Spionidae**	**Random Forest**	**0.97**	**Excellent**	**0.84**	**Excellent**
	Spionidae	GAM	0.92	Excellent	0.75	Very good
	Spionidae	MARS	0.89	Good	0.67	Very good
	Spionidae	BRT	0.89	Good	0.65	Very good
	Spionidae	GLM	0.75	Good	0.44	Good
150	**Tellinidae**	**Random Forest**	**0.97**	**Excellent**	**0.86**	**Excellent**
	Tellinidae	GAM	0.93	Excellent	0.79	Very good
	Tellinidae	MARS	0.9	Excellent	0.67	Very good
	Tellinidae	BRT	0.88	Good	0.61	Very good
	Tellinidae	GLM	0.8	Good	0.54	Good

3.2 Environmental variables influence on spatial distribution

Maximum salinity was the most influential environmental variable in predicting the spatial distribution of the main taxa such as Cirratulidae, Magelonidae and Orbiniidae (**Figure 3**). Minimum salinity proved to be the most influential variable for Nereididae. While for Paraonidae, Tellinidae Spionidae, salinity was less influential than mud (silt and clay) percentage in sediments.

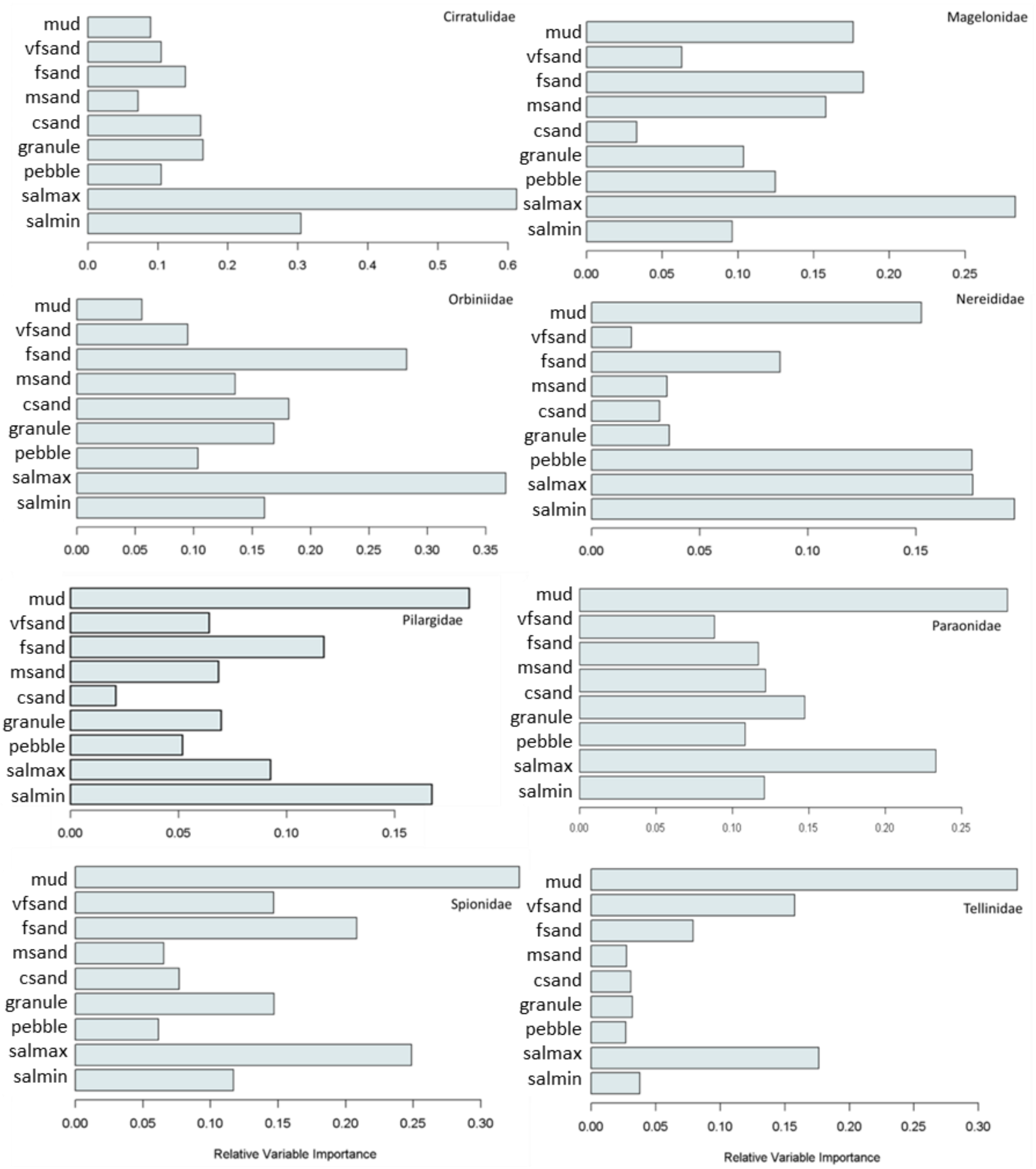

Figure 3. Influence of environmental variables in predicting faunal distribution. Higher values indicate higher importance in the model for salinity (minimum and maximum) and sediment (pebble, granule, csand: coarse sand, msand: medium sand, fsand: fine sand, vfsand: very fine sand and mud).

3.3 Saline intrusion effect on macrobenthos spatial distribution

The general trend obtained from the future scenarios simulations was a reduction in the taxa occurrence probability, in relation to the current scenario, and increase in the occurrence probability upstream (**Figure 4**). Model predictions indicated a greater reduction in the occurrence probability for the taxa Cirratulidae and Paraonidae in the euhaline zone. For the Magelonidae and Orbiniidae families the reduction occurred in the euhaline and polyhaline zones. For the Pilargidae family, a greater reduction was predicted in the mesohaline zone and for Nereididae in the oligohaline zone (**Figure 4**).

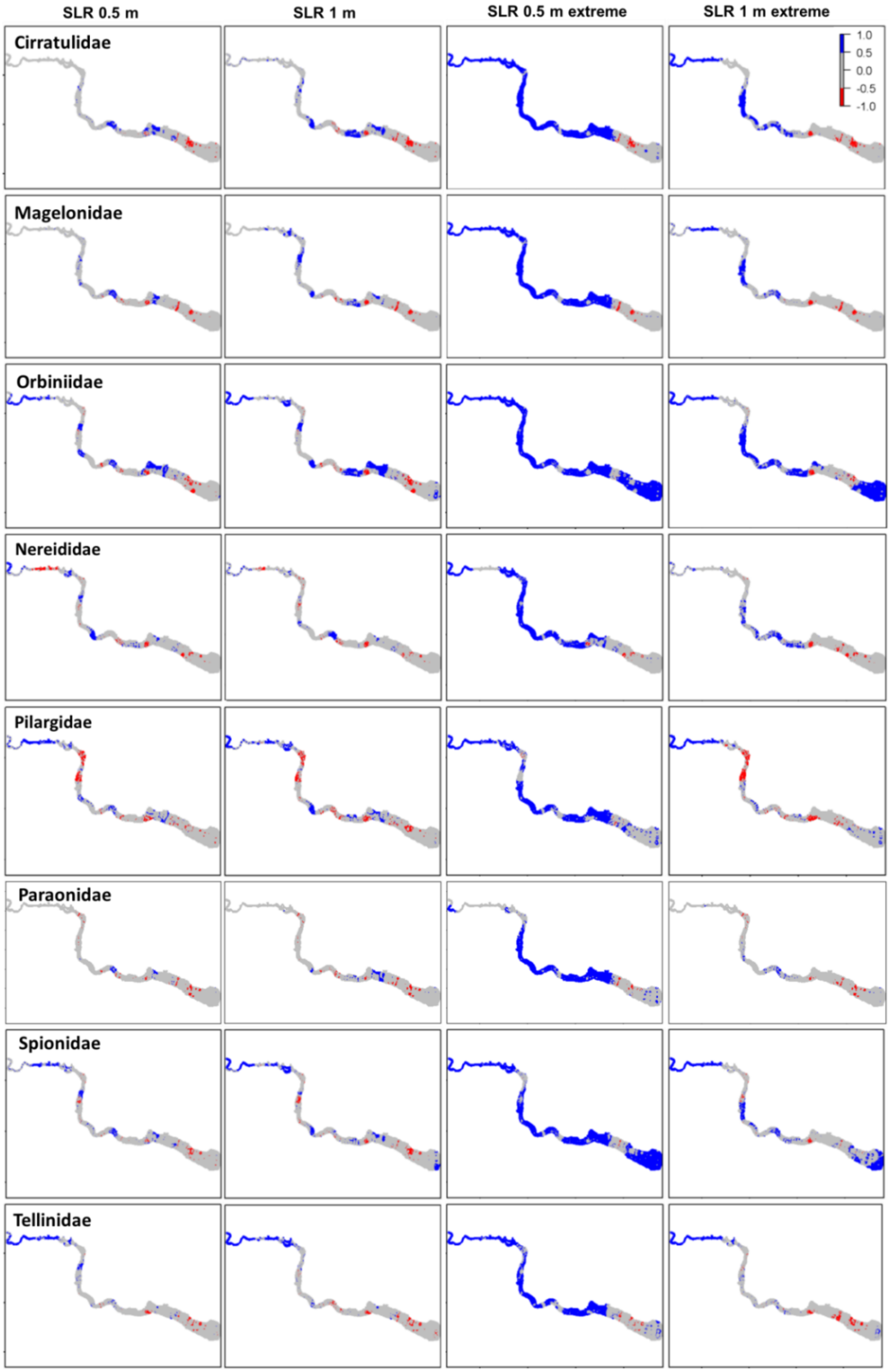

Figure 4. Changes in the occurrence probability of macroinvertebrate families for future (moderate and extreme) scenarios using the ensemble method. Zero indicates no

changes, 1 (blue) indicates expansion or colonization and -1 (red) indicates retraction or extinction.

3.4 Changes in taxa spatial distribution

In general, there was a significant change in the families' spatial distribution for all scenarios in relation to the baseline scenario, as indicated by Schoener's D index (**Figure 5**). The differences between the current and future scenarios were observed in the 1 m moderate and 0.5 m extreme scenarios. The families that showed the greatest changes in spatial distribution were Cirratulidae, Magelonidae, Orbiniidae and Paraonidae.

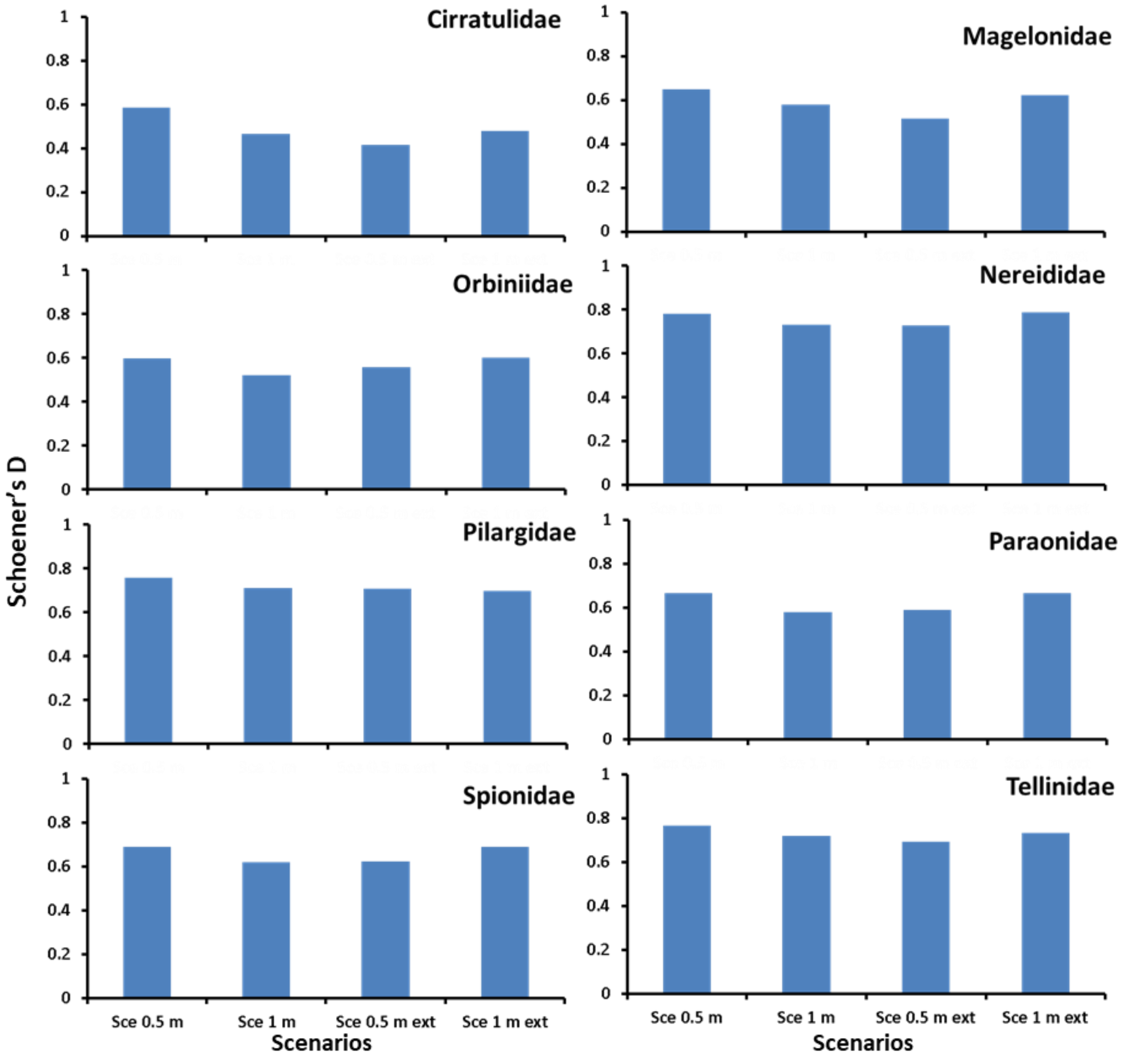

Figure 5. Changes in the families' spatial distribution using Schoener's D index for niche overlap. The x-axis represents elevation values (0.5 and 1 m) in moderate and extreme conditions. The y-axis represents the amount of change from the baseline scenario. Zero indicates no overlap in the niche models and 1 indicates that niche models are identical.

4 Discussion

4.1 Models performance

The high values of AUC and TSS indicate that the SDM represented a good tool for generating predictive models applicable to small-scale environments subject to strong gradients such as estuaries. Other small-scale studies in the marine and freshwater environment reinforce the potential of using SDM as an ecosystem management tool. For instance, SDM was used successfully in building species distribution maps for protected area management (Becker et al., 2020) and assess the impacts of environmental changes on faunal distribution in the recent past (i.e., 1970 to 2009) (Singer et al., 2016). In the freshwater environment, SDM was used to develop a management tool for detecting fish feeding sites and predicting the occurrence of exotic species using local influence variables (i.e., depth, sediment and flow velocity) (Mehler et al., 2017). The results obtained in this study show that, in addition to being useful for application on a small scale, it can be applied to environments with strong environmental gradients. Thus, Species Distribution Modeling represents an important predictive tool for dealing with problems where large-scale processes affect local scale. This type of information is essential for decision makers to feel prepared to plan climate change adaptation strategies (Thorne et al., 2017).

Random forest modeling proves to have the greatest predictive capacity compared to the other models. This is an expected result since this type of model is good in perform classifications (Breiman, 2001; Maxwell et al., 2018; Šiaulys and Bučas, 2012; Turner et al., 2018). The basic principle behind the random forest is that results obtained from many models with low predictive ability can perform better than a single model with high predictive ability. What makes this approach very useful at both constructing good predictive models and not overfitting datasets (Breiman, 2001; Elith et al., 2008). On the other hand, the worst performance was registered for simulations generated from GLM. It has already been demonstrated in comprehensive comparative studies that non-parametric models (e.g., boosted regression trees, maximum entropy modelling) have better performance than parametric and semi-parametric models (e.g., GLMs, GAMs) in species distribution models (Elith et al., 2006; Reiss et al., 2011). Gogina & Zettler (2010) applied the GLM method to model benthic invertebrates in the Baltic Sea and the authors pointed out the limited ability of GLMs to fit complex nonlinear relationships between species and environmental variables. As way of overcoming individual performance limitations, the use of the ensemble technique allowed us to combine the best contributions of the different models as has been highly recommended (Drake, 2014; Elith et al., 2008; Naimi and Araújo, 2016; Reiss et al., 2015).

4.2 Importance of environmental variables

As expected salinity was the environmental variable that most influenced the spatial distribution of most families. This is because salinity acts as an environmental filter, restricting the establishment of these marine organisms according to their physiological tolerance to lower salinities (Barros et al., 2012; Remane and Schlieper, 1971; Whitfield et al., 2012). Similarly, finer sediments such as mud were very important for most of the organisms studied. Finer sediments also act as constraint variables since they can subject organisms to anoxic conditions lead to the occurrence of severe oxygen depletion when subsurface organic matter is decomposed, consuming oxygen, and the smaller the distance between the grains reduces gas exchange between the water column and the sediment lower layers (Barnes, 1989; Gerwing et al., 2018; Moodley et al., 2011), especially rich in organic matter such as estuarine sediments (Pearson and Rosenberg, 1978; Yoshino et al., 2010). Sites with low-oxygen sediment require organisms to have physiological (i.e., tolerance) and/or behavioral (e.g., tube or burrowing) adaptations to survive in this type of habitat (Kristensen, 1983; Pearson and Rosenberg, 1978). Thus, organisms that have such characteristics can benefit from the low interaction (competition or predation) and colonize the environment (Montagna and Ritter, 2006). For instance, populations of these organisms (e.g., Nereididae and Spionidae) can often reach high abundance values, even in undisturbed environments due to the action of environmental filters that reduce biological interactions (e.g., predation and competition) (Botter-Carvalho et al., 2011).

4.3 Consequences of saline intrusion in distribution

Saline intrusion as a result of sea level rise is an expected trend for most estuaries around the globe (Mohammed & Scholz, 2018; Robins et al., 2016) and may be intensified by reduced rainfall and increased temperature as recently predicted for northeastern Brazil (IPCC, 2021). Such changes in salinity have great potential to modify the benthic fauna distribution in the medium term (i.e., with a 0.5 m scenario expected for 2050) (Little et al., 2017). Our results point to a trend towards colonization upstream from the euhaline region (e.g., Cirratulidae) while suggesting the local extinction of families occurring in the oligohaline region such as the Nereididae family that are known to have a higher tolerance to low salinities (e.g., Nereididae) (Mazurkiewicz, 1975; Prevedelli and Vandini, 1997). In the latter case, it is possible that local extinction occurs in parallel with colonization of new niches formed by saline intrusion upstream, having as restriction in the short term natural factors (geomorphology and substrate) and artificial (e.g., walls and dams) (Fujii and Raffaelli, 2008). Additionally, saline intrusion may allow other marine organisms that were previously prevented from colonizing the estuary because they do not have evolutionary mechanisms for tolerance to low salinity, to occupy this area (Smyth and Elliott, 2016). Hallett et al., (2018) studied extreme saline intrusion on estuaries and found that the main ecological effect of estuarine marinization was the increase of the typically marine species upstream. The authors pointed out the increase in interspecific interactions (predation and competition) as mechanism for ecosystem unbalance that can lead to exclusion (or extinction) of taxa that have important biological traits for the functioning of the estuarine ecosystem (Hallett et al., 2018; Hughes, 1984).

In contrast to the marine environment, where organisms subject to similar environmental conditions can be regulated mainly by biological interactions (e.g., predation and competition) (Solan and Whiteley, 2016), in the estuarine environment, restrictive environmental variables may play a more important role than biological interactions and act as environmental filters, influencing mainly estuarine longitudinal spatial distribution (Alves et al., 2020; Telesh et al., 2013b). Populations of organisms capable of overcoming environmental filters will be subject to conditions at the limit of their physiological tolerance in relation to such variables (Cartier et al., 2011; Montague and Ley, 1993; Pechenik et al., 2000) and they have to use strategies to minimize the biological interactions effects (e.g., habitat partitioning) (Flint and Kalke, 1986). Thus, it is expected that during the process of saltwater intrusion due to sea level rise, a greater number of taxa that previously did not have access to the innermost regions of the estuaries will be able to colonize upstream regions (Fujii and Raffaelli, 2008). In addition to the interaction with native species, organisms in estuaries will be more subject to competition and predation by invasive species that remarkably have adaptive advantages over native species (Ménesguen et al., 2018; Xue et al., 2018). Additionally, saline intrusion can result in changes in essential habitats for ecosystem functioning whose distribution is affected by the salinity gradient such as mangroves tree species (e.g., Costa et al., 2015). Consequently, the change in adjacent ecosystems and the intensification of biological interactions upstream by increasing diversity can compromise important roles played by estuarine ecosystems, such as the nursery of marine species (Brown et al., 2016; Lee et al., 2014; Vasconcelos et al., 2012; Attrill and Power, 2002).

4.4 Expected impact on estuarine functioning

Important ecological functions performed by estuaries (e.g., degradation of organic matter) (Basset et al., 2013; Quintino et al., 2009) aided by benthic invertebrates through biological traits (e.g., morphology, food habits and movement) (Kristensen et al., 2014) can be effected by salinity intrusion due their influence on spatial distribution of organisms (Little et al., 2017). For example, all studied organisms are burrowers and, thus, contribute to the sediment mobilization (Rouse and Pleijel, 2001) (See **Appendix C**). By producing their galleries, these organisms favor the flow of oxygen-rich water to the sediment layers (Queirós et al., 2015; Aubry and Elliott, 2006) resulting in the acceleration of the organic matter degradation process and incorporation of released nutrients into the food chain (Quintino et al., 2009). Changes in the spatial distribution of these organisms can contribute to the loss of this function (i.e., degradation of organic matter), contributing to the excessive accumulation of organic matter in the subsurface. As the degradation of organic matter consumes large amounts of oxygen, the absence of these organisms can lead to sediment anoxia, impacting foraging or even the local extinction of other species (Moodley et al., 2011). At the same time, changes in the spatial distribution of bioengineering organisms (e.g., Magelonidae, Cirratulidae and Spionidae) can affect sediment stabilization (Hooper et al., 2005) and promote erosion processes resulting from a new circulation regime forced by sea-level rise (Kuang et al., 2014) and bioeroding organisms (e.g., Nereididae) (Kristensen et al., 2013). Dietary traits contribute to top-down control, via consumption, of organisms such as bacteria, flagellates, diatoms, plankton and small animals (Jumars et al., 2015; Rouse & Pleijel, 2001; Jones & Wolff, 1981). At the same time these organisms will be consumed by various organisms with higher trophic level (e.g., birds, fish, crustaceans) (Wolansky and McLusky, 2012). Changes in the distribution of these organisms may impact secundary production and species that seek the estuary for food (Hallett et al., 2018). Furthermore, it may impact other ecosystems with strong connectivity such as coral reefs, whose fish depend on this ecosystem as a safe place for the early stages of their offspring (Brown et al., 2016).

5 Conclusion and recommendations

We conclude that changes in the spatial distribution of benthic macroinvertebrates in estuaries due to sea level rise at local scales can be successfully predicted by combining monitoring data and various predictive modeling techniques through species distribution modeling. Our results suggest that saline intrusion will result in taxa displacement upstream and extinction of some estuarine benthic invertebrates in future scenarios. In extreme scenarios of reduced rainfall and increased evaporation due to increased temperature as predicted by the IPCC in 2021, it is possible that shallow estuaries in tropical regions suffer a strong process of marinization. Future models (e.g., population dynamics) should focus on these new scenarios (i.e., rainfall reduction and increased evaporation) where changes in environmental filters distribution can favor competitive exclusion and predation in the structuring of the community including exotic species. Since macrobenthic fauna are essential for estuarine trophic webs, alterations in the distribution of benthic organisms can change the distribution of other species of commercial interest (e.g., fishes, shrimps, birds). With increasing necessity in obtaining forecasts at the local scale for management purposes, improvements can be reached using salinity and sediment distribution data from numerical simulations produced specifically for an estuary. In face of the effects of climate change at the local scale that can directly influence the lives of a large part of the human population, it is recommended the incorporation of numerical tools to predict effects and propose interventions in estuarine ecosystem management in order to minimize the ecological and social impacts of climate change. Our study showed that predictive species distribution modeling can be an important tool to assess possible future ecological changes in estuaries due to climate change effects. This tool can be very useful for the management and planning of adaptations to the effects of climate change on estuarine ecosystems.

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Appendix A

Data source and Sampling design

Data were obtained over 13 years (2006, 2007, 2009, 2010, 2014, 2016, 2019a and 2019b) where sediment samples containing the benthic macrofauna, sediment samples for determination of particle size classes and salinity data were collected. For the 2006, 2007, 2009, 2014, 2016 and 2019a campaigns, the design consisted of collecting macrofauna samples in 10 sampling stations (n = 8 replicates per station; total = 80 per campaign) using a 'corer' sampler (cylinder 10x15 cm). Additionally, sediment samples were collected and surface salinity measured with a refractometer, data logger and multiparameter probe in 10 georeferenced sampling stations distributed along the longitudinal section of the estuary. In the collections carried out in 2010 (n = 65 samples) and 2016 (n = 21 samples) the samples were collected using the same method at sampling points along the cross section of the estuary. The cross sections were distributed in different zones of the estuary (i.e., euhaline, polyhaline, mesohaline and oligohaline). Finally, in the 2019b campaign, biological samples were collected (total = 120 samples) randomly distributed in the different zones of the estuary (n = 10 per zone; n = 3 replicates per point) using a van veen grab sampler.

Sediment treatment

At each of the 10 sampling stations, sediment samples were collected with corer (5x10cm). In the laboratory, the samples were dried in an oven at 120 °C and the proportion of each sedimentological class in the sample was obtained by the sieving method, where the weight of the sediment retained in each sieve was obtained on an analytical balance. The classification of fractions was obtained using the method of Folk and Ward (Folk and Ward, 1957) using Sysgram software (Camargo, 2006)

Species occurrence

The distribution of each family (**Figure A.1**) was obtained by assigning the geographic coordinates (latitude and longitude) of the collection point to the record of the occurrence of the family in each sampling campaign.

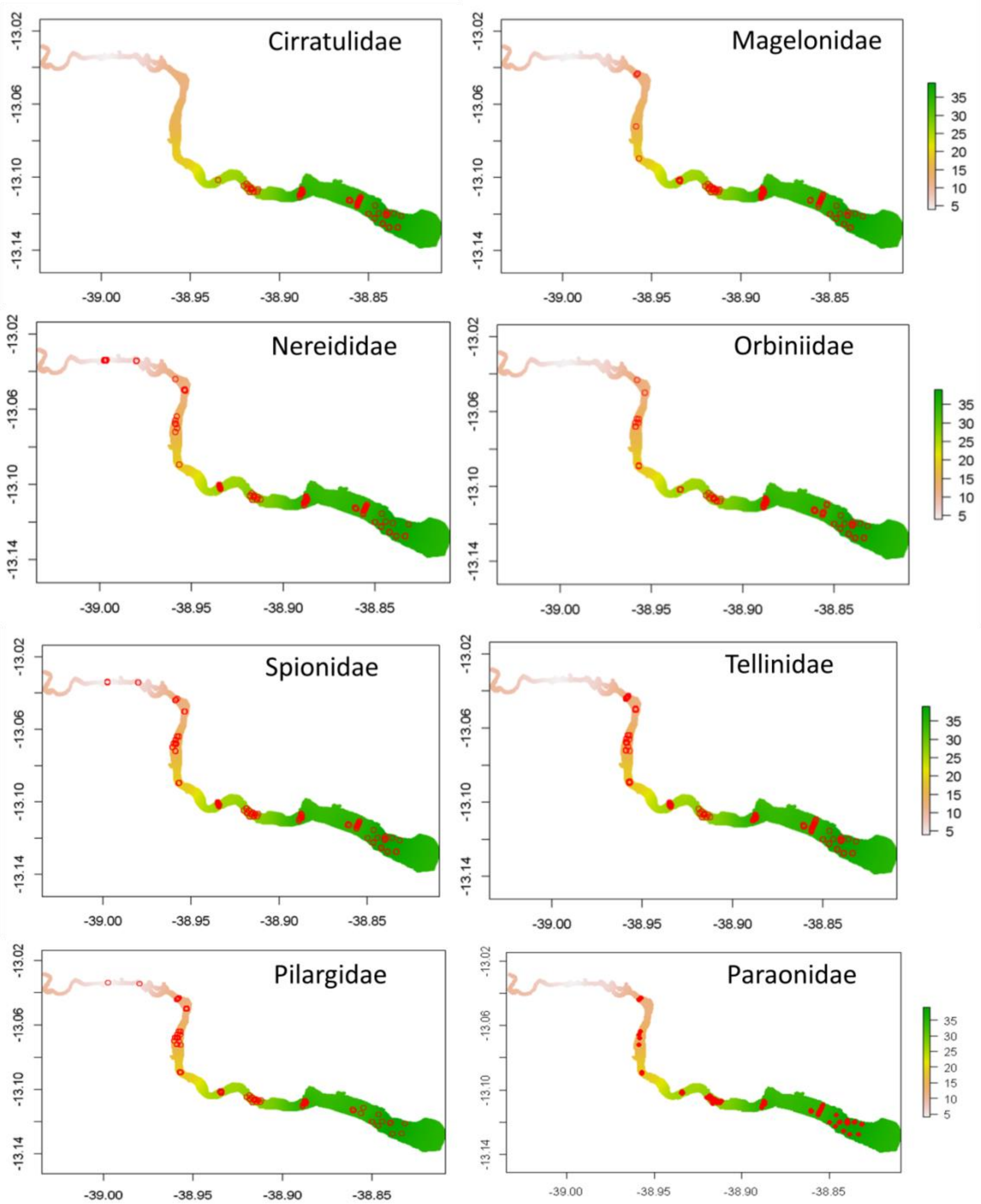

Figure A.1. Species occurrence for Cirratulidae, Magelonidae, Nereididae, Orbiniidae, Spionidae, Tellinidae, Pilargidae and Paraonidae. Gradient scale means maximum salinity values.

Surface salinity measurements (**Figure A.2**) were performed with a refractometer. According to the need for each campaign, additional measurements were performed using a multiparameter probe (Horiba®) and data loggers (HOBO®).

Salinity scenarios

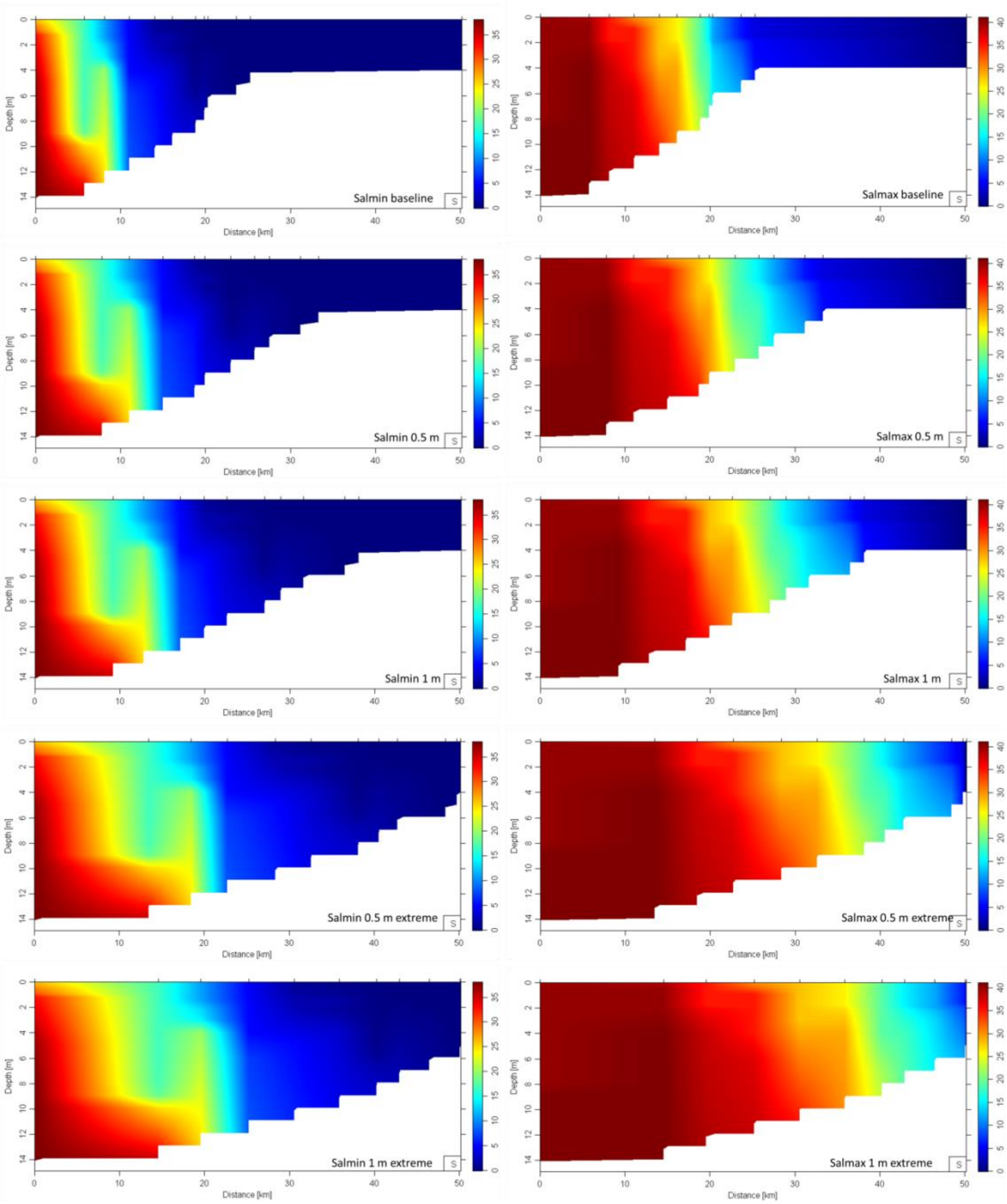

Figure A.2. Minimum and maximum salinity for the different scenarios in the Jaguaripe River estuary. The salinity representation for Jaguaripe was performed using the *oce* package (Kelley et al., 2020) on R software

Appendix B

Table B.1. Description of models used to predict macrozobentos distribution (Adapted from Reiss et al., 2015).

Modelling method	Description	Pros	Cons
GLM; Generalized Linear Model	Based on analysis of variance and covariance; various distributions and link functions used subject to the distribution features of both predictors and response variables (binomial for binary, Poisson for count data, negative binomial for overdispersed count data, logit for probability of binary response, etc.); from simple to multivariate regression	Variety of handled distributions, common, straightforward interpretation, high predictive power.	Model selection uncertainty and autocorrelation should be accounted for; the greater the flexibility (e.g. number of polynomials), the higher is the risk to overfit the data.
GAM; Generalized Additive Model	Straightforward extension of GLM where scatterplot smoothing functions (locally weighted mean) are used to build a sum of a set of arbitrary functions		Overfitting risk, complexity of interpretation suggests the use of sequence of non-parametric GAM to determine the dominant relationships and then apply parametric GLM for fine model fitting and prediction
MARS; Multivariate Adaptive Regression Splines	Non-parametric regression technique combines linear regression, mathematical construction of splines and binary response cursive partitioning to model (non-)linear relationships between environmental variables and species occurrence, coefficients differ across levels of predictor variables	Flexible, easy to interpret, automatically models non-linearities and interactions between variables	Does not give as good fits as boosted trees methods
RF; Random Forest	Uses collection of decision tree models to achieve top predictive performance	Ability to handle different types of variables and missing values, fitting interactions between predictors, immunity to extreme outliers	
BRT; Boosted Regression Trees	Boosting algorithm uses iterative forward stage wise modelling. Final model is developed by progressively adding simple CART trees by re-weighting data to emphasize cases poorly predicted by previous trees		

Appendix C

Taxa biological traits from Beesley et al., 2000, Fauchald, 1977, Jumars et al., 2015 and Rouse and Pleijel, 2001

Organisms of the Cirratulidae family are burrowing, tubiculous, surface and subsurface deposit feeders. It feeds mainly on detritus and diatoms with the help of palps. They are mostly found in high salinities (30 to 40 PSU). Are able to tolerate moderate salinities (18 to 30) and are found in lower abundance in salinities below 18. They are associated with sediments ranging from blocks, sandy and muddy sediments.

The Magelonidae family are excavators and tubiculous. They have varied food habits such as surface deposit feeders, suspension feeders and predators. Their diet varies between detritus, microalgae and small animals. They play an important role in bioturbation. Are found in greater abundance in high salinities (30-40) and may occur in moderate salinities (18-40 PSU). It has a greater affinity with sandy to muddy sediments.

Orbiniidae are crawling organisms, burrowing tubiculous and deposit feeders. They feed on detritus, diatoms and foraminiferans. They have an important role as biodiffusor. They are found in sediments that range from sandy to muddy.

Nereidiae are organisms of varied living habits. In relation to movement, it can be a swimmer, crawler and tubiculous. They are omnivores, depositivores, detritivores, active suspenders of suspended organic matter and predators. It plays an important role as a bioturbator and biodiffuser. Its tolerance to low salinity is high, being able to reach great abundance in salinities close to zero. It has an affinity for sandy-mud sediments.

Paraonidae are crawling and burrower organisms. They are deposit feeders and herbivores, feeding on bacteria, flagellates, diatoms, foraminifera and debris. They are biodiffusers and are associated with sandy sediments.

Spionidae are crawler, burrower and tubicolous. They are deposit and suspensory feeders, feeding on particulate matter, planktonic organisms, diatoms, meiofauna organisms and molluscs. They are preyed on by other annelids, fish, birds, molluscs and echinoderms. They have an affinity with sandy to muddy sediments. Can be found in blocks.

Tellinidae are active suspensive and deposit feeders on suspended and deposited phytoplankton, diatoms and debris. They are burrowers, crawlers and borrow dwelling. They have moderate tolerance to low salinity (18-40). They are associated with variety of sedimentary classes such as sediment mixtures containing coarse sand gravel and mud.

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Reiss, H., Birchenough, S., Borja, A., Buhl-mortensen, L., Craeymeersch, J., Dannheim, J., Darr, A., Galparsoro, I., Gogina, M., Neumann, H., Populus, J., Rengstorf, A.M., Valle, M., Hoey, G. Van, Zettler, M.L., Degraer, S., 2015. Benthos distribution modelling and its relevance for marine ecosystem management. ICES J. ofMarine Sci. 72, 297–315.

Rouse, G.W., Pleijel, F., 2001. Polychaetes, Polychaetes. Oxford University Press Inc., Oxford.

Conclusões Gerais

O objetivo desta tese foi contribuir para o entendimento sobre o uso de ferramentas ecológicas preditivas para investigação dos principais efeitos da elevação do nível do mar sobre a fauna bentônica em ecossistemas estuarinos. Este objetivo foi alcançado através de duas abordagens: i) a síntese da literatura que identificou as principais ferramentas ecológicas preditivas e os impactos causados pela elevação do nível do mar em estuários e ii) através de simulação computacional dos efeitos da intrusão salina sobre a fauna bentônica em um estuário real.

A síntese dos principais modelos ecológicos preditivos que utilizaram os organismos bentônicos para investigação de alterações ambientais mostrou que ao longo dos últimos quarenta anos os pesquisadores nos diferentes ambientes (i.e., marinho, estuarino e de água doce) contribuíram para consolidação deste tópico de pesquisa. Inicialmente os pesquisadores utilizaram abordagens e ferramentas distintas, motivados pela resolução de questões associadas à cultura de pesquisa já estabelecida nestes ambientes. Por exemplo, estudos preditivos em água doce estiveram associados principalmente a estudos de biomonitoramento como à previsão de distúrbios causados por ação humana e classificação da qualidade da água e do ecossistema. Estudos no ambiente marinho e estuarino focaram na implementação de teorias ecológicas em modelos preditivo para investigar sua efetividade no estudo da biodiversidade e relações ecológicas. Mais recentemente (últimos 20 anos), os estudos realizados nos diferentes ambientes passaram a utilizar ferramentas comuns e abordar temas mais gerais como efeitos de larga escala sobre ecossistemas locais (mudanças climáticas) e das espécies exóticas. Entre as ferramentas usadas é importante destacar a importância de parcerias institucionais para criação de programas de computador (e.g., Ecopath, RIVPACS) para resolução de questões específicas. Este tipo de iniciativa deve ser incentivada, principalmente pensando na gestão dos ecossistemas. Nos últimos anos, o software R tornou-se a ferramenta mais popular, possuindo aplicações em diversos temas, principalmente modelagem de distribuição de espécies e biomonitoramento. A modelagem preditiva de organismos bentônicos como tópico de pesquisa possui estratégias e ferramentas bem estabelecidas e ao longo do tempo incorporou novas ferramentas (e.g., R), técnicas (e.g., machine learning) e tem buscado respostas para questões emergentes como recuperação de ecossistemas, espécies invasoras e efeitos das mudanças climáticas sobre os ecossistemas aquáticos.

Os estudos que investigaram os efeitos da elevação do nível do mar sobre os estuários ao redor do globo apontaram que a intrusão salina e a inundação dos terrenos adjacentes ao estuário são os impactos mais preocupantes. A intrusão salina em particular foi um efeito bastante estudado e modelos computacionais hidrodinâmicos mostraram que a elevação do nível do mar possui influência direta sobre essa intrusão. Adicionalmente, estes estudos destacaram o papel da vazão dos rios neste processo e para o risco de que em cenários futuros de baixa vazão o resultado seja a hipersalinização do estuário. Os estudos que avaliaram os efeitos ecológicos mostraram que a inundação e intrusão salina podem contribuir para a perda da biodiversidade, biomassa, favorecer o estabelecimento de espécies exóticas e interferir em serviços ecossistêmicos importantes como estocagem de carbono. Além disso, a intrusão salina poderá causar prejuízos econômicos como a captação de água para abastecimento, indústria e agricultura. Poucos estudos apresentaram simulações dos efeitos de intervenções com intuito de mitigar os efeitos da intrusão salina em estuários. As simulações realizadas com objetivo de avaliar a eficiência de intervenções para a redução da velocidade das correntes por meio da construção de diques submersos ou impedir a propagação da intrusão salina através de barragens se mostraram ineficazes no médio prazo. Tais intervenções podem causar sérios danos ao ecossistema estuarino como inundações, hipersalinização e criação de planícies salinas adjacentes ao estuário. Simulações de possíveis intervenções para mitigação dos impactos da intrusão salina e inundações são extremamente complexas, devem ser mais encorajadas e contar com a inclusão de gestores públicos.

O uso de modelos preditivos para investigação dos efeitos da intrusão salina sobre a distribuição espacial de macroinvertebrados bentônicos no estuário do Jaguaripe apresentou resultados muito satisfatórios. Estes resultados não haviam sido alcançados antes para a pequena escala no gradiente de salinidade estuarino. A previsão do modelo indicou que a intrusão salina como resultado da elevação do nível do mar poderá induzir alterações na distribuição da macrofauna bentônica. Especificamente para o estuário do Rio Jaguaripe a progressiva elevação do nível do mar poderá provocar a colonização de zonas mais internas do estuário, com extinção local na região originalmente habitada. A migração desses organismos para regiões mais internas pode resultar em um fenômeno conhecido como marinização do estuário, onde espécies marinhas que antes eram impedidas de acessar regiões internas do estuário passam a colonizar este ambiente, como consequência é esperado o aumento das interações ecológicas como competição e predação, resultando em exclusão dessas espécies. Modelos preditivos com foco nas interações ecológicas (e.g., modelos de redes tróficas) podem ser usados para explorar este tipo de cenário. Uma vez que a fauna macrobentônica é um nível essencial das teias tróficas estuarinas, mudanças na distribuição de organismos bentônicos podem alterar a distribuição de outras espécies de interesse comercial (e.g., peixes, siris, camarões). Estudos ecológicos futuros podem aprimorar a acurácia de suas previsões ao utilizar os resultados de modelos computacionais hidrodinâmicos na exploração de cenários de alteração das variáveis ambientais (e.g., salinidade, sedimento, nutrientes). Este estudo mostrou que a modelagem ecológica preditiva da fauna bentônica pode ser uma ferramenta importante para avaliar os impactos de mudanças ambientais futuras. Esta ferramenta pode ser muito útil para a gestão e planejamento de adaptações aos efeitos das mudanças climáticas nos ecossistemas estuarinos.

Supplementary Material

Chapter 1: General trends after forty years of predictive models applied to benthic macroinvertebrates from marine, estuarine and freshwater environment

The information extracted from the articles used in the systematic review can be consulted in the electronic spreadsheet:

Table 1: “*Chapter 1 Table 1_Eco_Models*.xls”

Chapter 2: Trends of sea-level rise effects on estuaries: A quali-quantitative synthesis in toward for a simple general model to estimate future saline intrusion in estuaries

The information used in the quali-quantitative sysnthesis can be consulted in the electronic spreadsheet:

Table 1: “*Chapter 2 Table 1*.xls”

- In the "Papers" tab you will find information regarding the studies (e.g., publication date, title, authors, affiliation).
- The "Map" tab contains information about the distribution of studies in the world. This information was used for the elaboration of figure 4.
- The “Saline Intrusion” tab contains the data for quantitative analysis that represents the relationship between sea-level rise, saline intrusion and river flow.

Chapter 3: Sea-level rise effects on macrozoobenthos distribution in the estuarine gradient using Species Distribution Modeling

Data source and Sampling design

Data were obtained over 13 years (2006, 2007, 2009, 2010, 2014, 2016, 2019a and 2019b) where sediment samples containing the benthic macrofauna, sediment samples for determination of particle size classes and salinity data were collected. For the 2006, 2007, 2009, 2014, 2016 and 2019a campaigns, the design consisted of collecting macrofauna samples in 10 sampling stations (n =

8 replicates per station; total = 80 per campaign) using a 'corer' sampler (cylinder 10x15 cm). Additionally, sediment samples were collected and surface salinity measured with a refractometer, data logger and multiparameter probe in 10 georeferenced sampling stations distributed along the longitudinal section of the estuary. In the collections carried out in 2010 (n = 65 samples) and 2016 (n = 21 samples) the samples were collected using the same method at sampling points along the cross section of the estuary. The cross sections were distributed in different zones of the estuary (i.e., euhaline, polyhaline, mesohaline and oligohaline). Finally, in the 2019b campaign, biological samples were collected (total = 120 samples) randomly distributed in the different zones of the estuary (n = 10 per zone; n = 3 replicates per point) using a van veen grab sampler.

Sediment treatment

At each of the 10 sampling stations, sediment samples were collected with corer (5x10cm). In the laboratory, the samples were dried in an oven at 120 °C and the proportion of each sedimentological class in the sample was obtained by the sieving method, where the weight of the sediment retained in each sieve was obtained on an analytical balance. The classification of fractions was obtained using the method of Folk and Ward (Folk and Ward, 1957) using Sysgram software (Camargo, 2006)

Species occurrence

The distribution of each family (**Figure 1**) was obtained by assigning the geographic coordinates (latitude and longitude) of the collection point to the record of the occurrence of the family in each sampling campaign.

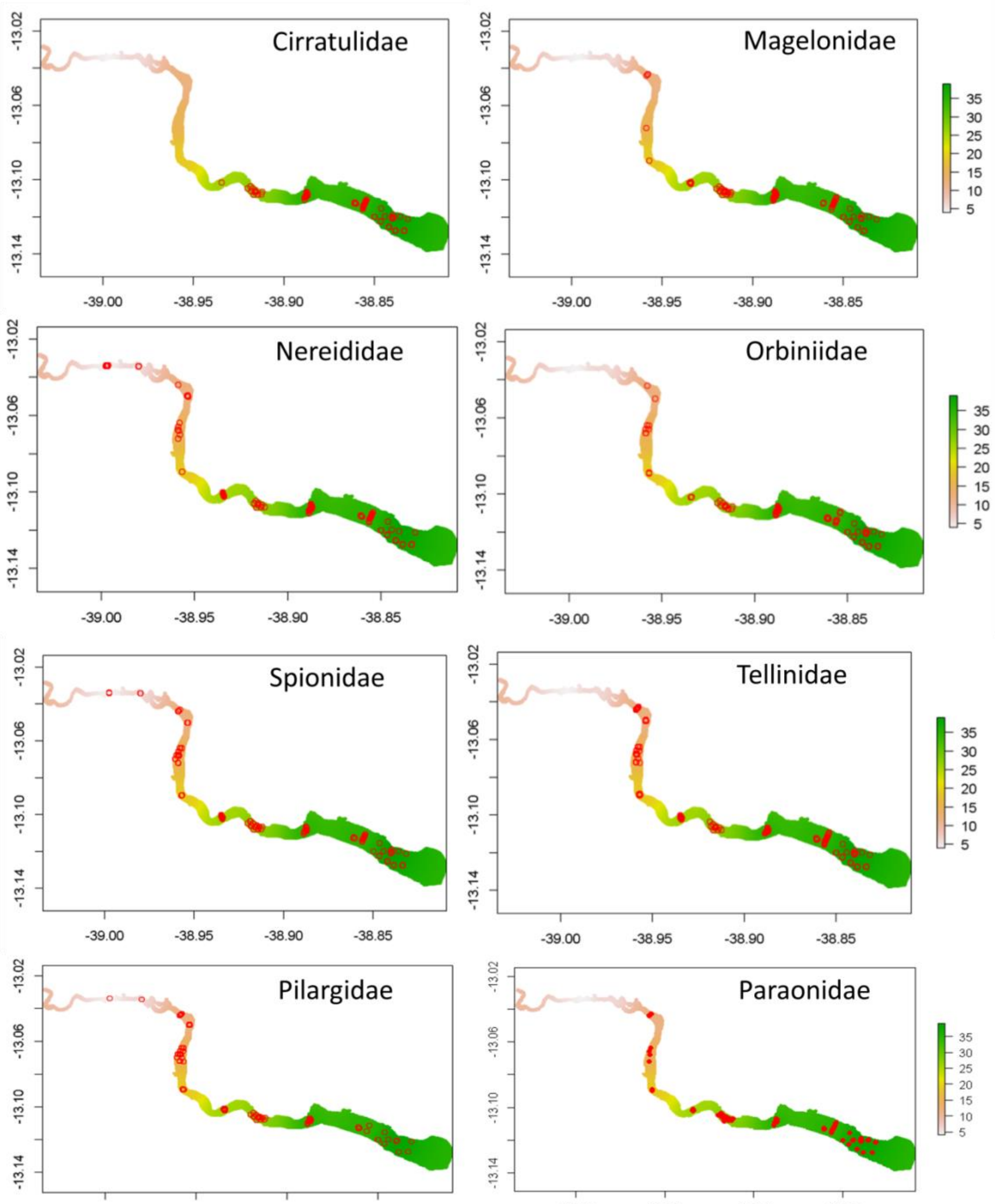

Figure 2. Species occurrence for Cirratulidae, Magelonidae, Nereididae, Orbiniidae, Spionidae, Tellinidae, Pilargidae and Paraonidae. Gradient scale means maximum salinity values.

Surface salinity measurements (**Figure 2**) were performed with a refractometer. According to the need for each campaign, additional measurements were performed using a multiparameter probe (Horiba®) and data loggers (HOBO®).

Salinity scenarios

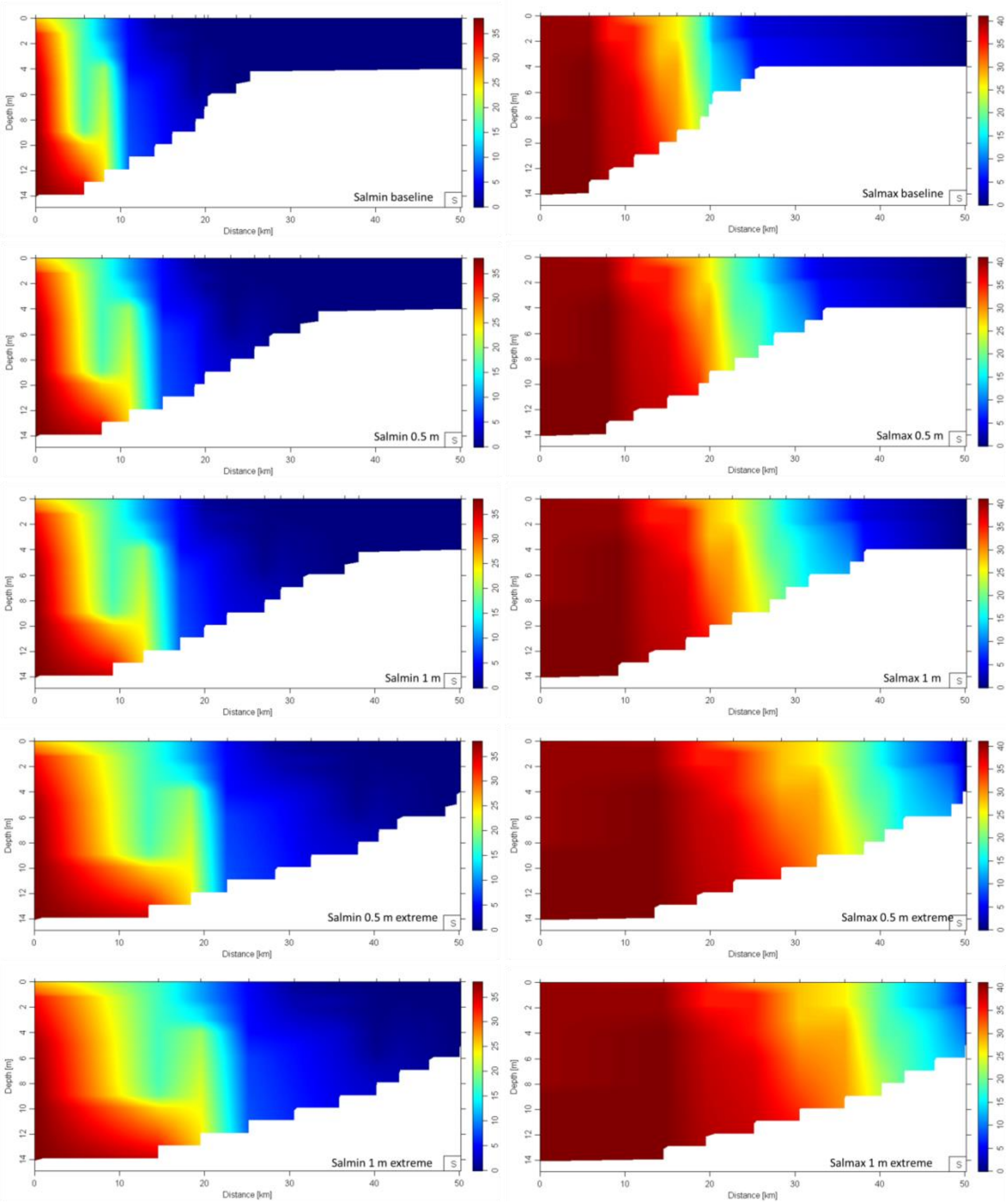

Figure 3. Minimum and maximum salinity for the different scenarios in the Jaguaripe River estuary. The salinity representation for Jaguaripe was performed using the *oce* package (Kelley et al., 2020) on R software

Table 1. Description of models used to predict macrozobentos distribution (Adapted from Reiss et al., 2015).

Modelling method	Description	Pros	Cons
GLM; Generalized Linear Model	Based on analysis of variance and covariance; various distributions and link functions used subject to the distribution features of both predictors and response variables (binomial for binary, Poisson for count data, negative binomial for overdispersed count data, logit for probability of binary response, etc.); from simple to multivariate regression	Variety of handled distributions, common, straightforward interpretation, high predictive power.	Model selection uncertainty and autocorrelation should be accounted for; the greater the flexibility (e.g. number of polynomials), the higher is the risk to overfit the data.
GAM; Generalized Additive Model	Straightforward extension of GLM where scatterplot smoothing functions (locally weighted mean) are used to build a sum of a set of arbitrary functions		Overfitting risk, complexity of interpretation suggests the use of sequence of non-parametric GAM to determine the dominant relationships and then apply parametric GLM for fine model fitting and prediction
MARS; Multivariate Adaptive Regression Splines	Non-parametric regression technique combines linear regression, mathematical construction of splines and binary response cursive partitioning to model (non-)linear relationships between environmental variables and species occurrence, coefficients differ across levels of predictor variables	Flexible, easy to interpret, automatically models non-linearities and interactions between variables	Does not give as good fits as boosted trees methods
RF; Random Forest	Uses collection of decision tree models to achieve top predictive performance	Ability to handle different types of variables and missing values, fitting interactions between predictors, immunity to extreme outliers	
BRT; Boosted Regression Trees	Boosting algorithm uses iterative forward stage wise modelling. Final model is developed by progressively adding simple CART trees by re-weighting data to emphasize cases poorly predicted by previous trees		

Taxa biological traits from Beesley et al., 2000, Fauchald, 1977, Jumars et al., 2015 and Rouse and Pleijel, 2001

Organisms of the Cirratulidae family are burrowing, tubiculous, surface and subsurface deposit feeders. It feeds mainly on detritus and diatoms with the help of palps. They are mostly found in high salinities (30 to 40 PSU). Are able to tolerate moderate salinities (18 to 30)and are found in lower abundance in salinities below 18. They are associated with sediments ranging from blocks, sandy and muddy sediments.

The Magelonidae family are excavators and tubiculous. They have varied food habits such as surface deposit feeders, suspension feeders and predators. Their diet varies between detritus, microalgae and small animals. They play an important role in bioturbation. Are found in greater abundance in high salinities (30-40) and may occur in moderate salinities (18-40 PSU). It has a greater affinity with sandy to muddy sediments.

Orbiniidae are crawling organisms, burrowing tubiculous and deposit feeders. They feed on detritus, diatoms and foraminiferans. They have an important role as biodiffusor. They are found in sediments that range from sandy to muddy.

Nereidiae are organisms of varied living habits. In relation to movement, it can be a swimmer, crawler and tubiculous. They are omnivores, depositivores, detritivores, active suspenders of suspended organic matter and predators. It plays an important role as a bioturbator and biodiffuser. Its tolerance to low salinity is high, being able to reach great abundance in salinities close to zero. It has an affinity for sandy-mud sediments.

Paraonidae are crawling and burrower organisms. They are deposit feeders and herbivores, feeding on bacteria, flagellates, diatoms, foraminifera and debris. They are biodiffusers and are associated with sandy sediments.

Spionidae are crawler, burrower and tubicolous. They are deposit and suspensory feeders, feeding on particulate matter, planktonic organisms, diatoms, meiofauna organisms and molluscs. They are preyed on by other annelids, fish, birds, molluscs and echinoderms. They have an affinity with sandy to muddy sediments. Can be found in blocks.

Tellinidae are active suspensive and deposit feeders on suspended and deposited phytoplankton, diatoms and debris. They are burrowers, crawlers and borrow dwelling. They have moderate tolerance to low salinity (18-40). They are associated with variety of sedimentary classes such as sediment mixtures containing coarse sand gravel and mud.

References

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Rouse, G.W., Pleijel, F., 2001. Polychaetes, Polychaetes. Oxford University Press Inc., Oxford.

R Code

Cirratulidae

YuriCosta

16/06/2021

Sea-Level Rise effects on benthos in estuarine ecosystems using Species Distribution Modeling

The purpose of this script is to describe the ecological niche modeling steps carried out to investigate sea-level rise effects on benthic macroinvertebrates in estuarine ecosystems.

Installing packages

The codes used for simulation consist of ecological niche modeling packages (sdm), geospatial to deal with environmental layers (raster, sf), tables (dplyr) and figure generation package (ggplot2).

```
# install.packages("sdm")    # Species distribution modeling package
# library(sdm)               # To use the installAll function
# installAll()               # Install all dependencies
# install.packages("sp")     # To work with shape file
# install.packages("raster") # To work with raster (ASCII) file
# install.packages("dplyr")  # To work with tables
# install.packages("tidyr")  # To work with tables
```

Loading packages

```
library(sp)
library(raster)
library(usdm)
library(dismo)
library(dplyr)
library(tidyr)
library(shiny)
```

```
library(sf)
```

Get biological data

Loading spcies occurence data

```
spp<- read.csv("occur_ab_spp_all.csv", sep = ";")


head(spp)
##          site longitude  latitude    species abundance
## 1      J01a2a -38.83341 -13.12746 Acteonidae         2
## 2      J01a2c -38.83338 -13.12755 Acteonidae         2
## 3      J01a5a -38.83136 -13.12115 Acteonidae         1
## 4 JP#01_2019 -38.83980 -13.12090 Albuneidae         1
## 5      J01b1a -38.83834 -13.12743  Alpheidae         1
## 6      J01b5c -38.83559 -13.11987  Alpheidae         1
```

Filtering interest species

```
cirratulidae <- subset(spp, species=="Cirratulidae", select= c(species
, longitude, latitude, abundance))
```

The number of rolls for this taxa is 91. Inspecting the spatial distribution of the taxa, the record was observed to have a point of occurrence containing only 1 specimen in an area of the estuary for which no other records were obtained. This record has been deleted to avoid including noise in the model.

```
##          species longitude  latitude abundance
## 406 Cirratulidae -38.95895 -13.04419         1
```

First, we find occurrence point to exclude based on latitude.

```
max(cirratulidae$latitude)
## [1] -13.04419
cir<-subset(cirratulidae, latitude!= max(cirratulidae$latitude))
```

After this process the number of rolls is 90. Let's look the filtered data.

```
##          species longitude  latitude abundance
## 319 Cirratulidae -38.83980 -13.12050         4
## 320 Cirratulidae -38.84020 -13.12050        13
## 321 Cirratulidae -38.84000 -13.12010        12
## 322 Cirratulidae -38.83940 -13.12050        10
```

```
## 323 Cirratulidae -38.83341 -13.12746         7
## 324 Cirratulidae -38.83348 -13.12753        11
```

Preparing the data

The first step is to remove NA's rolls.

```
sp<- cir                # putting species value in a generic vector.
sp<- cir %>% drop_na() # Removing rolls containing NA values.
```

There is 0 rolls containing NA values.

Preparing species geographical data for species. This data contains latitude and longitude information and add reference value to represent species.

```
spg <- sp %>% select(longitude, latitude)


spg$species <- 1
```

Now, we create a "SpatialPointsDataFrame" matrix object

```
coordinates(spg) <- c('longitude', 'latitude')
```

Get environmental data

In this section, we used environmental layers from the monitoring database. The first data included in the simulation were salinity (minimum and maximum) for the baseline scenario and 0.5m and 1m for moderate and extreme scenarios.

Salinity data

Baseline scenario (SLR 0 m)

Loading raster file in '.ascii' format.

```
salminbaseline <- raster("envlayers/salmin.asc")
salmaxbaseline <- raster("envlayers/salmax.asc")
```

Future scenarios

Moderate scenarios

The moderate scenarios were obtained using the predict function on SLR model versus salinity increment model.

```
# 0.50m SLR scenario  SLR moderado
salmin050 <- raster("envlayers/salminsce050.asc")
salmax050 <- raster("envlayers/salmaxsce050.asc")

# 1m SLR Scenario moderado
salmin1m <- raster("envlayers/salminsce1m.asc")
salmax1m <- raster("envlayers/salmaxsce1m.asc")
```

Extreme scenarios

The extreme scenarios were obtained from the model prediction interval of the SLR versus salinity increment model.

```
# 0.50m SLR Extreme scenario
salmin050ext <- raster("envlayers/salmin050ext.asc")
salmax050ext <- raster("envlayers/salmax050ext.asc")

# 1m SLR Extreme scenario
salmin1mext <- raster("envlayers/salmin1mext.asc")
salmax1mext <- raster("envlayers/salmax1mext.asc")
```

Sediment

The sediment layers (pebble, granule, very coarse sand, coarse sand, medium sand, fine sand, very fine sand and mud) were the same for all simulation scenarios.

```
pebble <- raster("envlayers/pebble.asc")       # Pebble
granule <- raster("envlayers/granule.asc")     # Granule
vcsand <- raster("envlayers/vcssand.asc")      # Very Fine Sand
csand <- raster("envlayers/csand.asc")         # Coarse Sand
msand <- raster("envlayers/msand.asc")         # Medium Sand
fsand <- raster("envlayers/fsand.asc")         # Fine Sand
vfsand <- raster("envlayers/vfsand.asc")       # Very Fine sand
mud <- raster("envlayers/mud.asc")             # Mud (Coarse Silt and c
lay)
```

Stacking layers

The environmental raster layers were put together into a single r object.

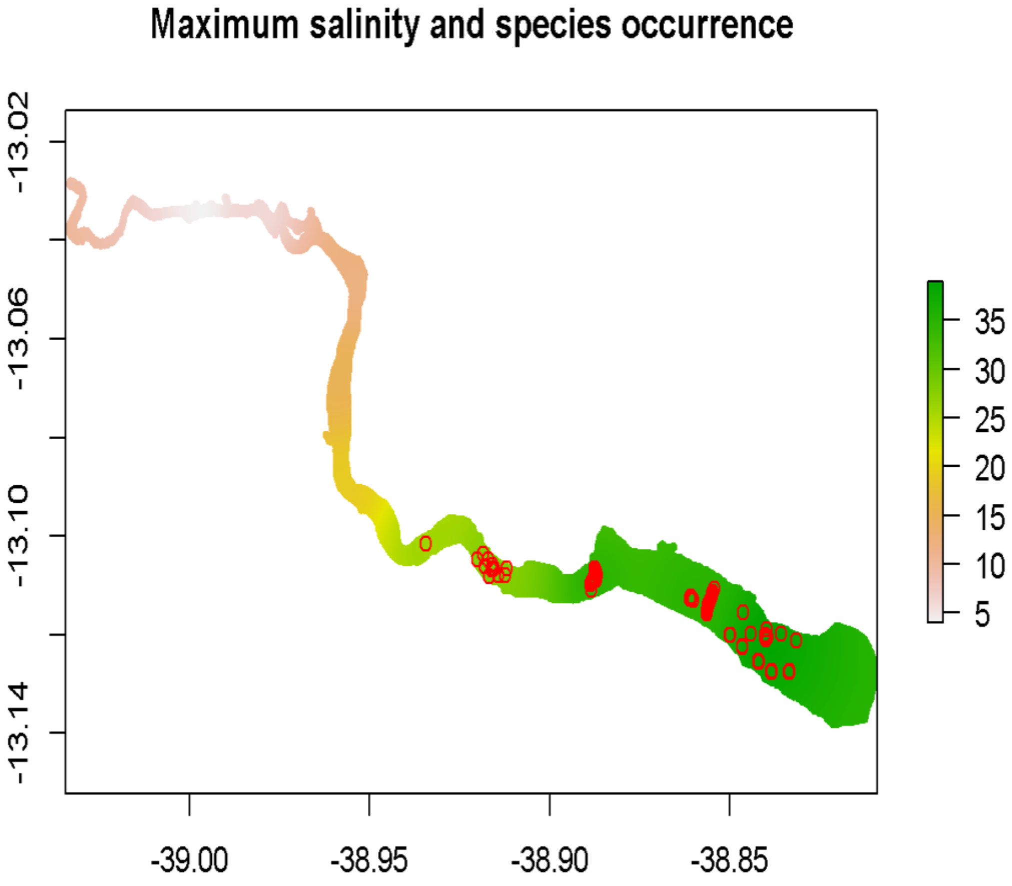
```
envbaseline <- stack( salminbaseline, salmaxbaseline,
```

```
                 pebble, granule, vcsand, csand, msand, fsand, vfsand, mu
d)
```

Visualizing layers and species occurrence

Plotting maximum salinity and occurrence for Cirratulidae on Jaguaripe estuary.

```
plot(envbaseline[[2]], main="Maximum salinity and species occurrence")
points(spg, col= "red")
```



Evaluating environmental layers multicollinearity

The multicollinearity was evaluated by considering environmental data related to species occurrence. Thus, multicollinearity was investigated for the taxa Cirratulidae. The first step was to extract environmental values from occurrence points.

Data extraction

Here we created an object called ‘ex’ to keep the extracted values.

```
ex <- raster::extract(envbaseline, spg)
```

Multicollinearity analysis

The multicollinearity analysis method used was the VIF (Variance Inflation Factor). The VIF method determines the strength of the correlation between independent variables. It is predicted by taking one variable and regressing it against all other variables. This analysis was applied on the ‘ex’ object to obtain the variables most correlated with each other.

```
v <- vifstep(ex)
## 1 variables from the 10 input variables have collinearity problem:
##
## vcssand
##
## After excluding the collinear variables, the linear correlation coe
fficients ranges between:
## min correlation ( csand ~ salmax ):  0.003699734
## max correlation ( granule ~ pebble ):  0.9143079
##
## ---------- VIFs of the remained variables --------
##   Variables      VIF
## 1    salmin 5.269894
## 2    salmax 5.087673
## 3    pebble 6.362427
## 4   granule 7.198731
## 5     csand 2.857778
## 6     msand 5.666423
## 7     fsand 4.101032
## 8    vfsand 3.535946
## 9       mud 2.088451
```

- VIF starts at 1 and has no upper limit
- VIF = 1, no correlation between the independent variable and the other variables
- VIF exceeding 5 or 10 indicates high multicollinearity between this independent variable and the others

Fixing Multicollinearity

The multicollinearity was fixed by removing the most correlated variables. In this case, was the variable vcssand

```
envbaseline2 <- exclude(envbaseline, v)
```

Performing Species Niche Modeling for baseline scenario

The Species niche model was created using sdm package (Naimi and Araújo, 2016) available for R software (R Development Core Team, 2016).

```
library(gbm)
library(sdm)
```

Creating Species Niche Modeling data

The Species Niche Modeling used to model Cirratulidae on Jaguaripe estuary were occurrence data (*spg*) and their respective environmental data obtained after multicollinearity evaluation. The method to generate 'pseudoabsenses' was grandom.

```
d <- sdmData(species~., spg,
             predictors = envbaseline2,
             bg = list(method='gRandom', n=1000))
```

Creating the model for Species Niche Modeling

To perform Species Niche Modeling was used the *sdm* function from sdm package. The most used methods to perform species niche modeling were used in order to compare the methods performance.

```
library(parallel)

m <- sdm(species~., d, methods=c('rf', 'brt', 'glm', 'gam', 'mars'),
         replication= c('sub', 'boot'),
         test.p=30, n=3,
         parallelSettings= list(ncore=4, method='parallel'))
```

Results

Relative variable importance

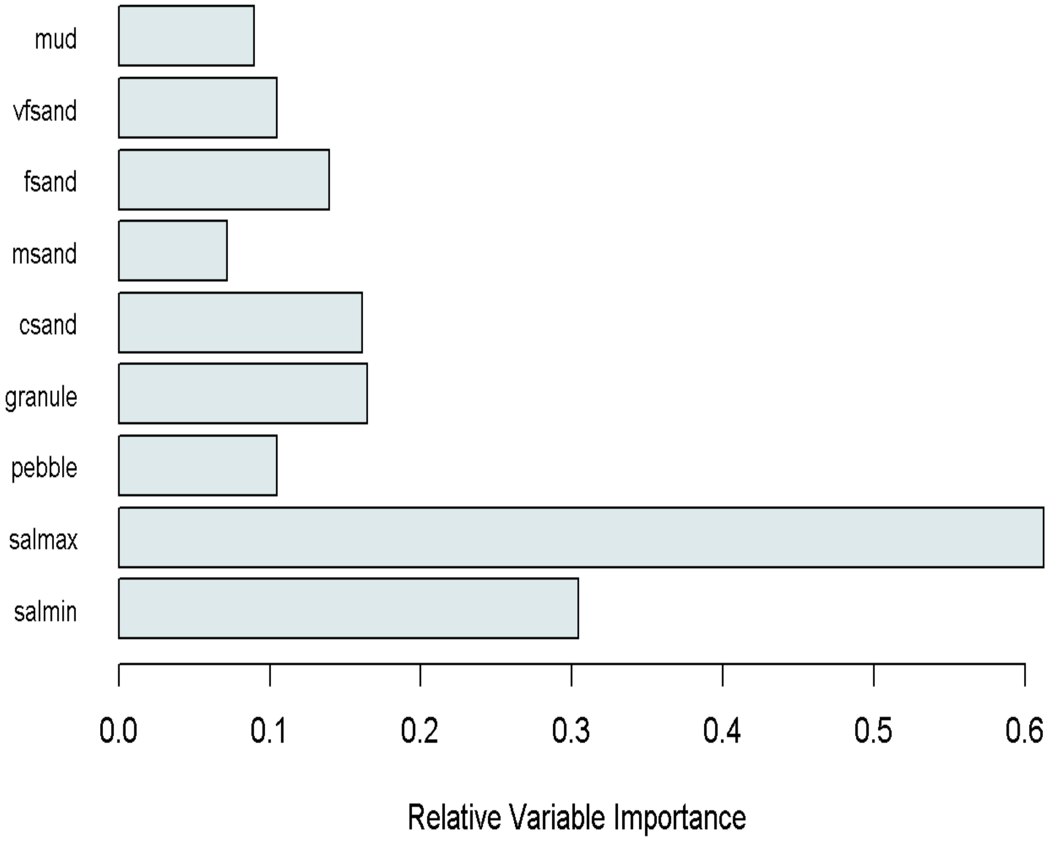
Create a summary based on Correlation or AUC metric

```
getVarImp(m, id=1)
```

```
## Relative Variable Importance
## =============================================================
## method               : Permutation based on two metrics (Pearson Cor
relation and AUC)
## number of variables :  9
## variable names      :  salmin, salmax, pebble, granule, csand, msan
d, fsand, vfsand, mud, ...
## =============================================================
## Relative variable importance
## ----------------------------------------------
## Based on Correlation metric:
## ----------------------------------------------
## salmin               : *************** (30.4 %)
## salmax               : ******************************* (61.3 %)
## pebble               : ***** (10.4 %)
## granule              : ******** (16.4 %)
## csand                : ******** (16.1 %)
## msand                : **** (7.1 %)
## fsand                : ******* (13.9 %)
## vfsand               : ***** (10.5 %)
## mud                  : **** (8.9 %)
## =============================================================
## Based on AUC metric:
## ----------------------------------------------
## salmin               : ******** (15.5 %)
## salmax               : ******************** (40.2 %)
## pebble               : *** (6.8 %)
## granule              : *** (6.5 %)
## csand                : **** (7.2 %)
## msand                : ** (4.9 %)
## fsand                : *** (5.5 %)
## vfsand               : *** (6.9 %)
## mud                  : *** (6.6 %)
## =============================================================
```

Plot Relative importance variables based on Correlation metric

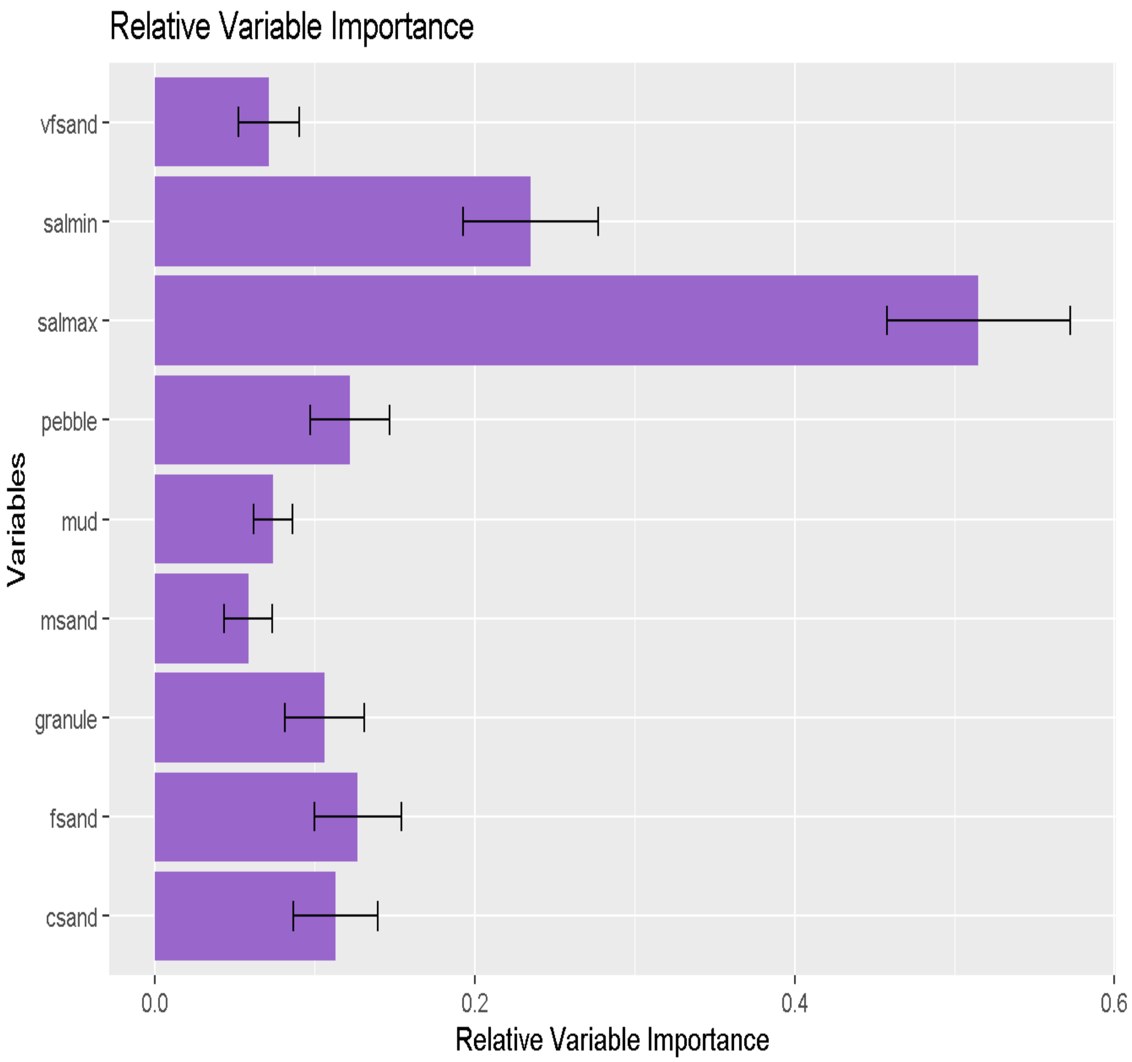
```
plot(getVarImp(m, id=1))
```



Using correlation metric was observed that most important variables for Cirratulidae are maximum salinity, minimum salinity, fine sand and coarse sand.

Plot Relative importance variables obtained by Random forest method

```
plot(getVarImp(m, method= 'rf'))
##
## The values of relative variable importance are generated from 6 mod
els...
```

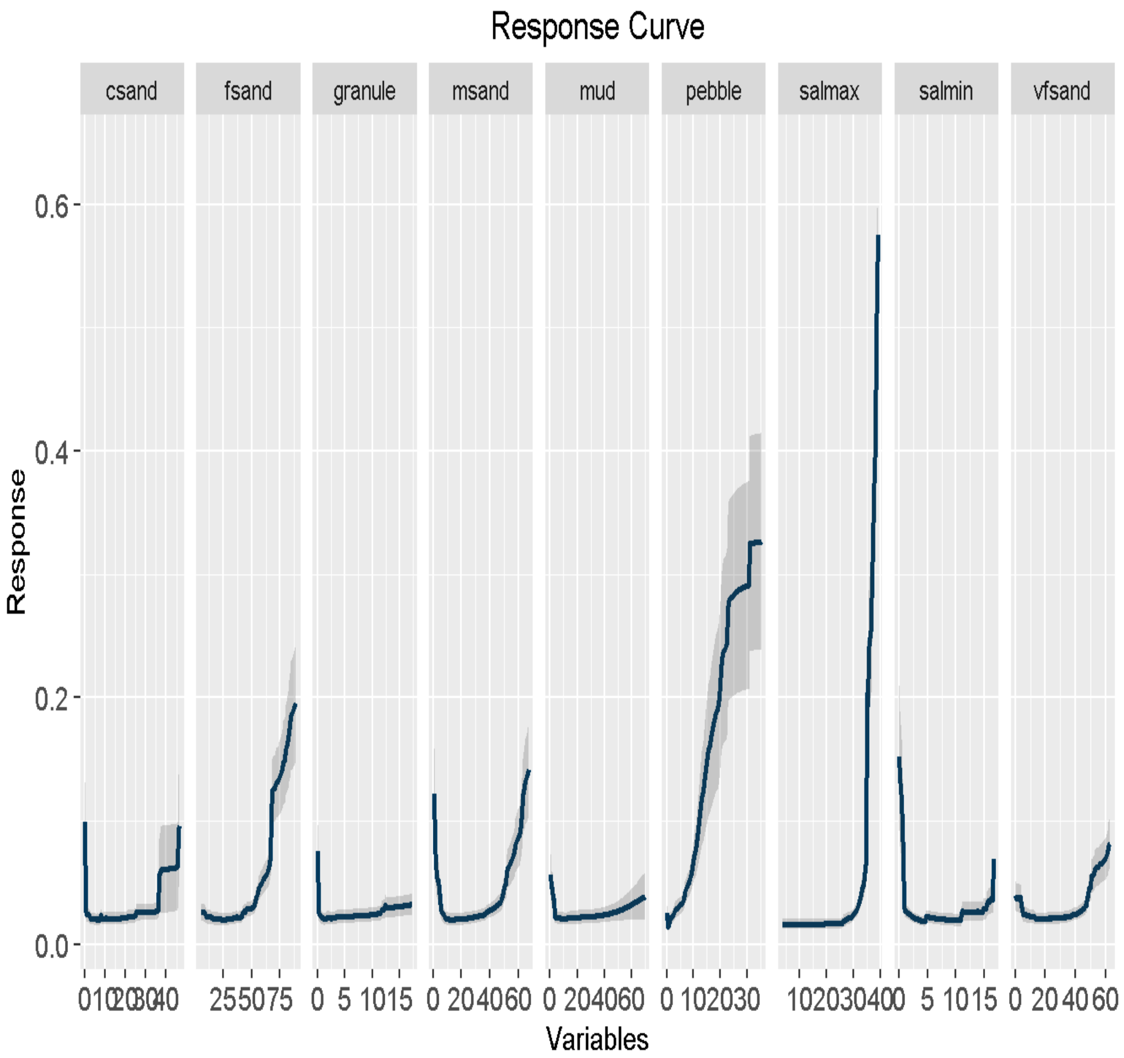


Visualizing response curves

Here we obtain the response curves

```
rcurve(m)
```

```
## The id argument is not specified; The modelIDs of 30 successfully f
itted models are assigned to id...!
```



Predict species distribution for baseline scenario

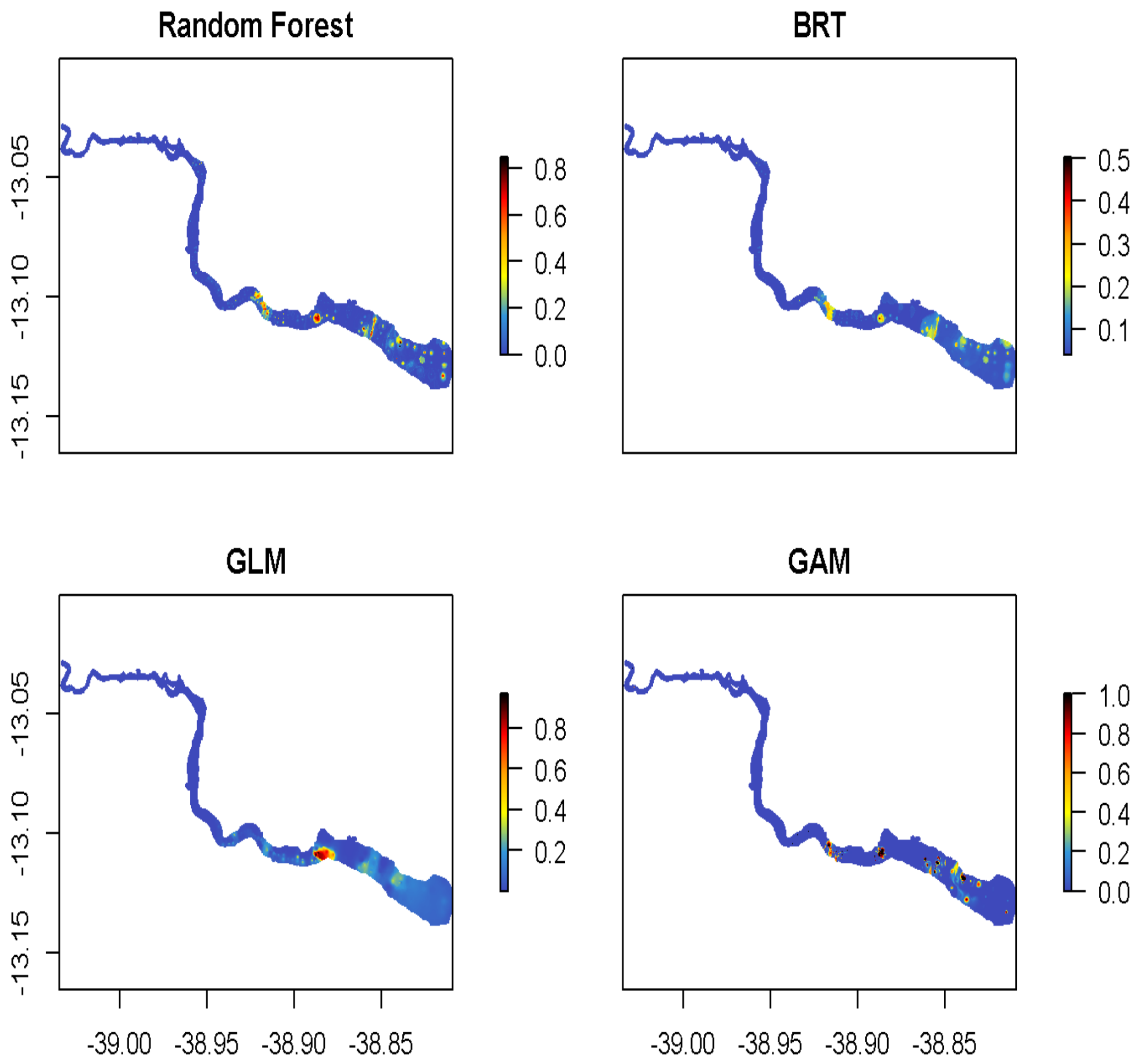
Were created the object called *predbaseline* considering the model *m* and environmental variables *envbaseline2* to represent the baseline distribution scenario for the species.

```
 library(sdm)


predbaseline <- predict(m, envbaseline2, filename='output/predbaseline
.img', overwrite=TRUE)
```

Models contribution evaluation

```
plot(predbaseline[[c(1, 7, 13, 19)]],
     main = c("Random Forest", "BRT", "GLM", "GAM"), col=cl(200))
```



Now we can integrate the results of all models.

Ensemble for baseline scenario

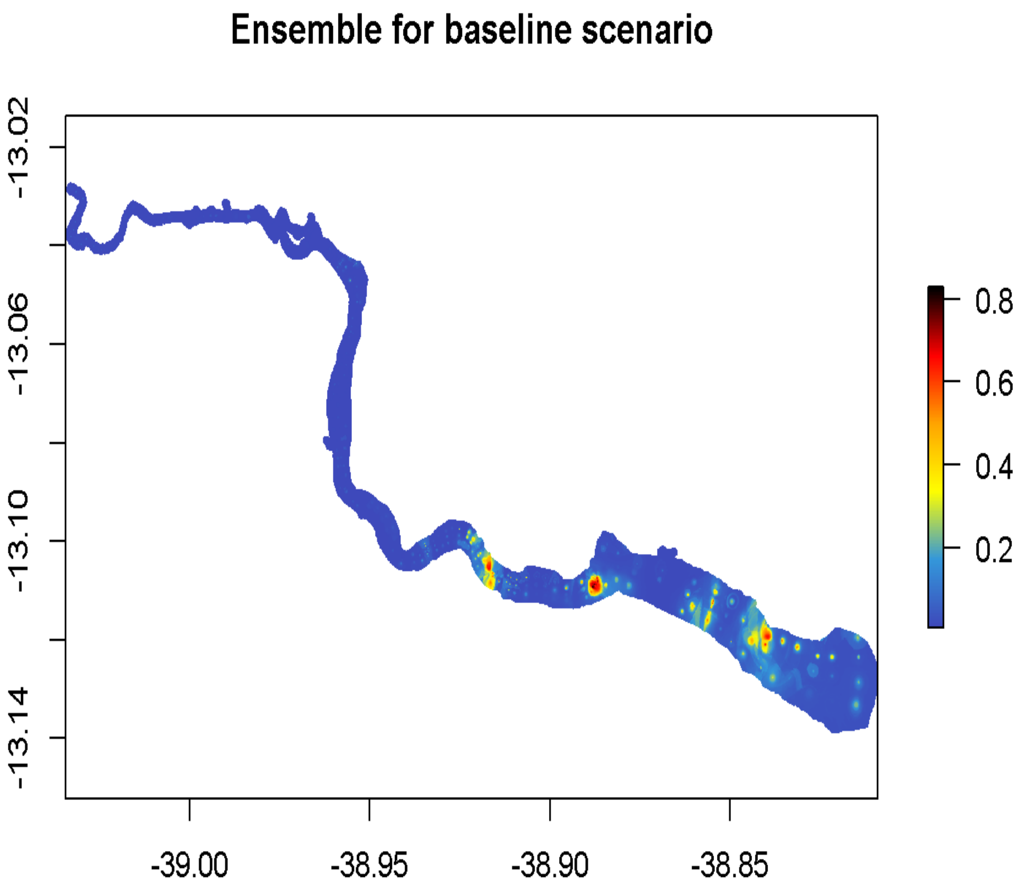
The ensemble model for baseline scenario was performed using ‘m’ and ‘predbaseline’. This procedure combines the best results of the different models.

```
ensemble1<- ensemble(m, predbaseline, filename='output/ensemblebaselin
e.img',
                          setting = list(method='weighted', stat='tss', opt
=2))
```

```
##
##  ......... the Raster object is used as the predicted probabilities
...
```

Here was plotted the results for ensemble model for baseline scenario.

```
plot(ensemble1, col=cl(200), main= 'Ensemble for baseline scenario')
```



Predict distribution for the future scenarios

Here we stack the layers without the layers (vcssand) indicated by multicollinearity analysis.

Stacking layers for the Moderate scenario

```
envf050 <- stack( salmin050, salmax050, pebble, granule, csand, msand,
fsand, vfsand, mud)

envf1m <- stack( salmin1m, salmax1m, pebble, granule, csand, msand, fs
and, vfsand, mud)
```

Stacking layers for the Extreme scenario

```
envf050ext <- stack( salmin050ext, salmax050ext, pebble, granule, csan
d, msand, fsand, vfsand, mud)
```

```
envf1mext <- stack( salmin1mext, salmax1mext, pebble, granule, csand,
msand, fsand, vfsand, mud)
```

To perform future prediction we must change future layers names to the same names of the baseline scenario.

```
# Moderate scenario

names(envf050) <- names(envbaseline2)

names(envf1m) <- names(envbaseline2)


# Extreme scenario

names(envf050ext) <- names(envbaseline2)

names(envf1mext) <- names(envbaseline2)
```

Creating ensemble predictive models for future scenarios

Moderate scenario

```
enf50 <-ensemble(m, envf050, filename='output/enf050.img', setting=lis
t(method='Weighted', stat='tss', opt='2'))

enf1m <-ensemble(m, envf1m, filename='output/enf1m.img', setting=list(
method='Weighted', stat='tss', opt='2'))
```

Extreme scenario

```
enf50ext <-ensemble(m, envf050ext, filename='output/enf050ext.img', se
tting=list(method='Weighted', stat='tss', opt='2'))

enf1mext <-ensemble(m, envf1mext, filename='output/enf1mext.img', sett
ing=list(method='Weighted', stat='tss', opt='2'))
```

Explore future scenarios results

We created a stack object to keep the ensemble results for future predictions.

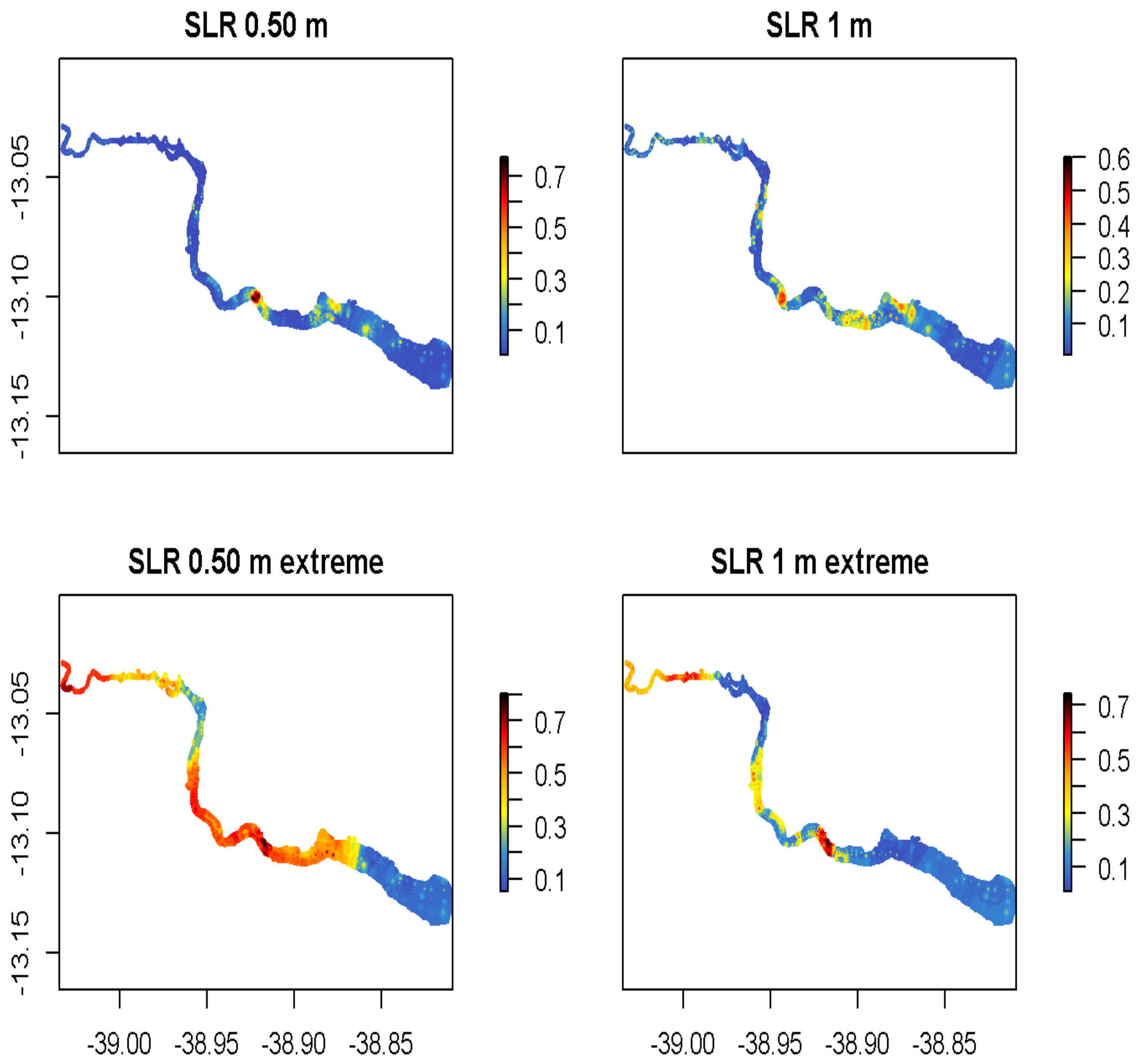
```
ens_future <- stack(enf50, enf1m, enf50ext, enf1mext)
```

Plot ensemble results for future (moderate and extreme scenarios)

```
plot(ens_future[[c(1,2,3,4)]],

     col=cl(200),

     main= c("SLR 0.50 m","SLR 1 m", "SLR 0.50 m extreme","SLR 1 m ext
reme"))
```



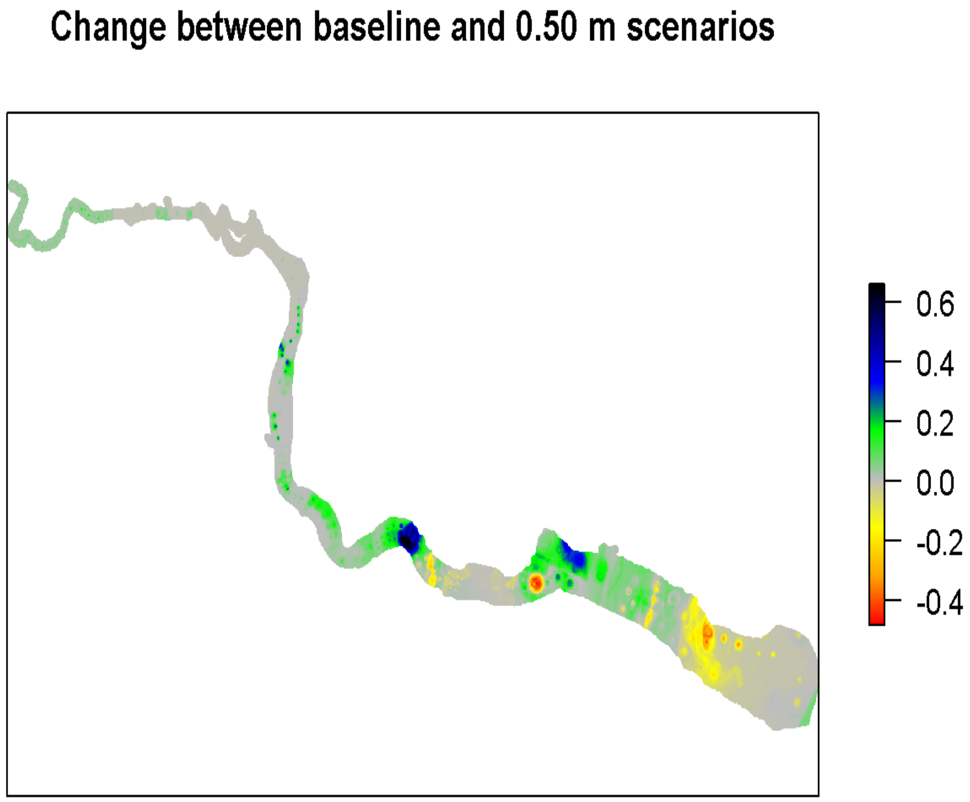
Quantifying differences between baseline, 0.50m and 1m for moderate scenarios

Calculate the changes between 0.5m and baseline scenario We can calculate the differences between scenarios using simple math operations.

```
change1 <- enf50 - ensemble1
```

Now we can plot the changes between baseline and the 0.5m SLR scenario. In this plot red and yellow colors represents suitability reduction, green and blue regions means suitability growth and gray regions shows regions where there is no change.

```
plot(change1,
     main="Change between baseline and 0.50 m scenarios",
     axes=FALSE, col=cl8(200))
```



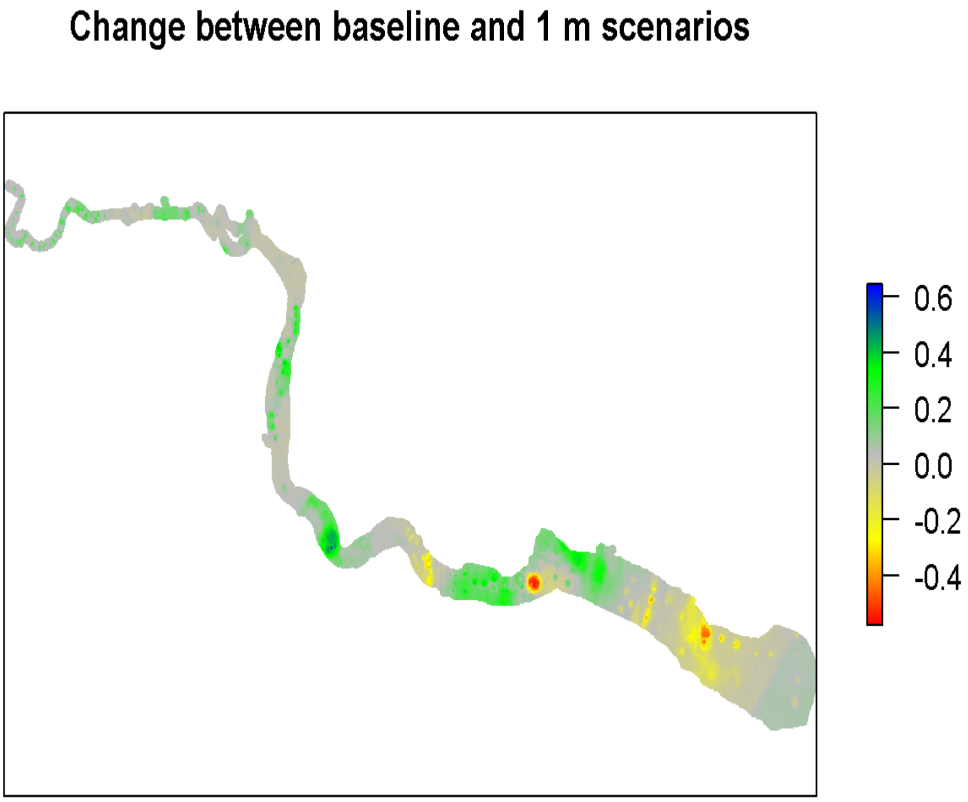
Calculate the changes between 1m and baseline scenario

We can also perform this process using a *overlay* function. It is useful in cases where the rasters are too large.

```
change2<- overlay(enf1m,
                  ensemble1,
                  fun=function(r1, r2){return(r1-r2)})
```

Now we can plot the changes between baseline and the 1m SLR scenario

```
# Plot output change
plot(change2,
     main="Change between baseline and 1 m scenarios",
     axes=FALSE, col=cl5(200))
```



Niche overlap analysis

To evaluate the future prediction variation related with baseline scenario we performed the niche overlap analysis (Warren *et al*, 2008). The metric used was Schoener's D.

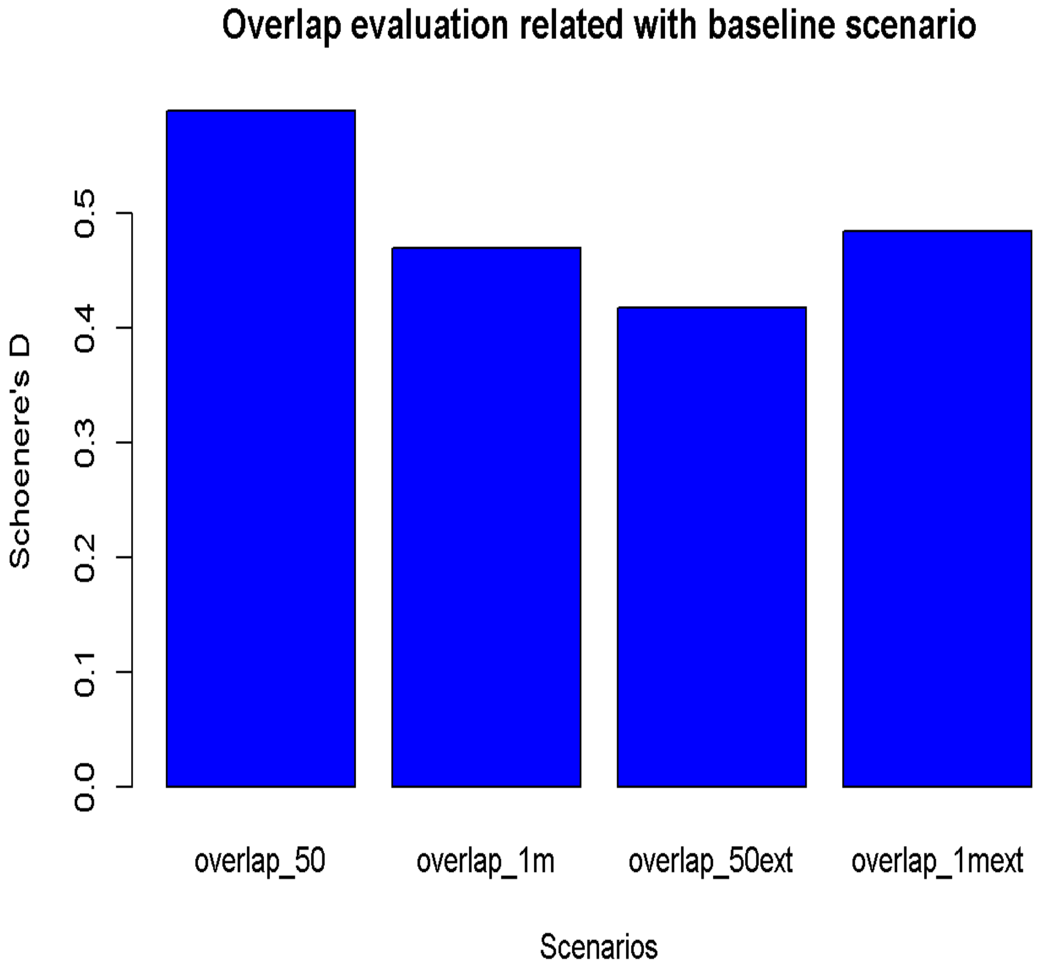
```
library(dismo)


overlap_50 <- nicheOverlap(ensemble1, enf50, stat='D', mask=TRUE, chec
kNegatives = TRUE)

overlap_1m <- nicheOverlap(ensemble1, enf1m, stat='D', mask=TRUE, chec
kNegatives = TRUE)

overlap_50ext <- nicheOverlap(ensemble1, enf50ext, stat='D', mask=TRUE
, checkNegatives = TRUE)

overlap_1mext <- nicheOverlap(ensemble1, enf1mext, stat='D', mask=TRUE
, checkNegatives = TRUE)
```



Now we can compare the results for each scenario

###**Schoenerer's (1968) statistic for niche overlap**

- 0 *Niche models have no overlap*
- 1 *Niche models identical*

Converting occurrence probability in presence-absence

Preparing the data

```
df <- as.data.frame(d)
df <- data.frame(species=df$species, coordinates(d))
xy<- as.matrix(df[,c('longitude', 'latitude')])
```

Extracting suitability values from *ensemble1* prediction for baseline scenario.

```
p<- raster::extract(ensemble1, xy)
```

```
ev<- evaluates(df$species, p)
```

Quantifying differences using threshold

Convert suitability prediction from baseline and future scenarios to presence-absence based on threshold.

```
th <- ev@threshold_based$threshold[2]
```

Create an empty raster with the same extent as the baseline raster to receive the results.

```
pa_baseline <- raster(ensemble1)
pa_enf50 <- raster(enf50)
pa_enf1m <- raster(enf1m)
pa_enf50ext <- raster(enf50ext)
pa_enf1mext <- raster(enf1mext)
```

Converting occurrence probability (suitability) in presence-absence

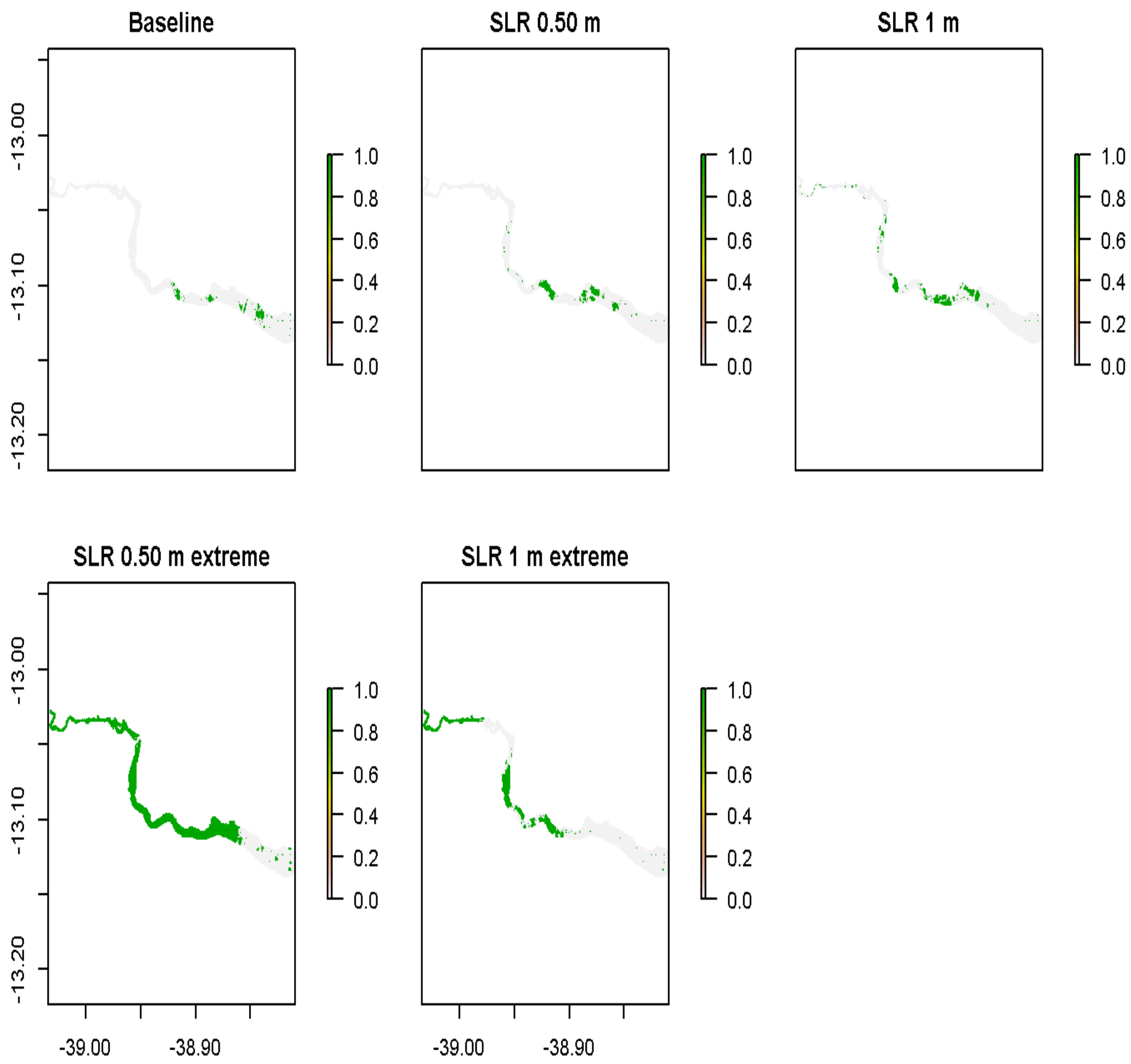
```
pa_baseline[] <- ifelse(ensemble1[] >= th, 1, 0)
pa_enf50[] <- ifelse(enf50[] >= th, 1, 0)
pa_enf1m[] <- ifelse(enf1m[] >= th, 1, 0)
pa_enf50ext[] <- ifelse(enf50ext[] >= th, 1, 0)
pa_enf1mext[] <- ifelse(enf1mext[] >= th, 1, 0)
```

Plot changes considering presence-absence data

Comparing baseline and future scenario

```
pa_all <- stack(pa_baseline, pa_enf50, pa_enf1m, pa_enf50ext, pa_enf1m
ext)


plot(pa_all[[c(1,2,3,4,5)]],
          main= c("Baseline","SLR 0.50 m","SLR 1 m", "SLR 0.50 m extre
me","SLR 1 m extreme"))
```



Calculate changes for presence-absence results

Calculate changes

```
ch_enf50 = pa_enf50 - pa_baseline
ch_enf1m = pa_enf1m - pa_baseline
ch_enf50ext = pa_enf50ext - pa_baseline
ch_enf1mext = pa_enf1mext - pa_baseline
```

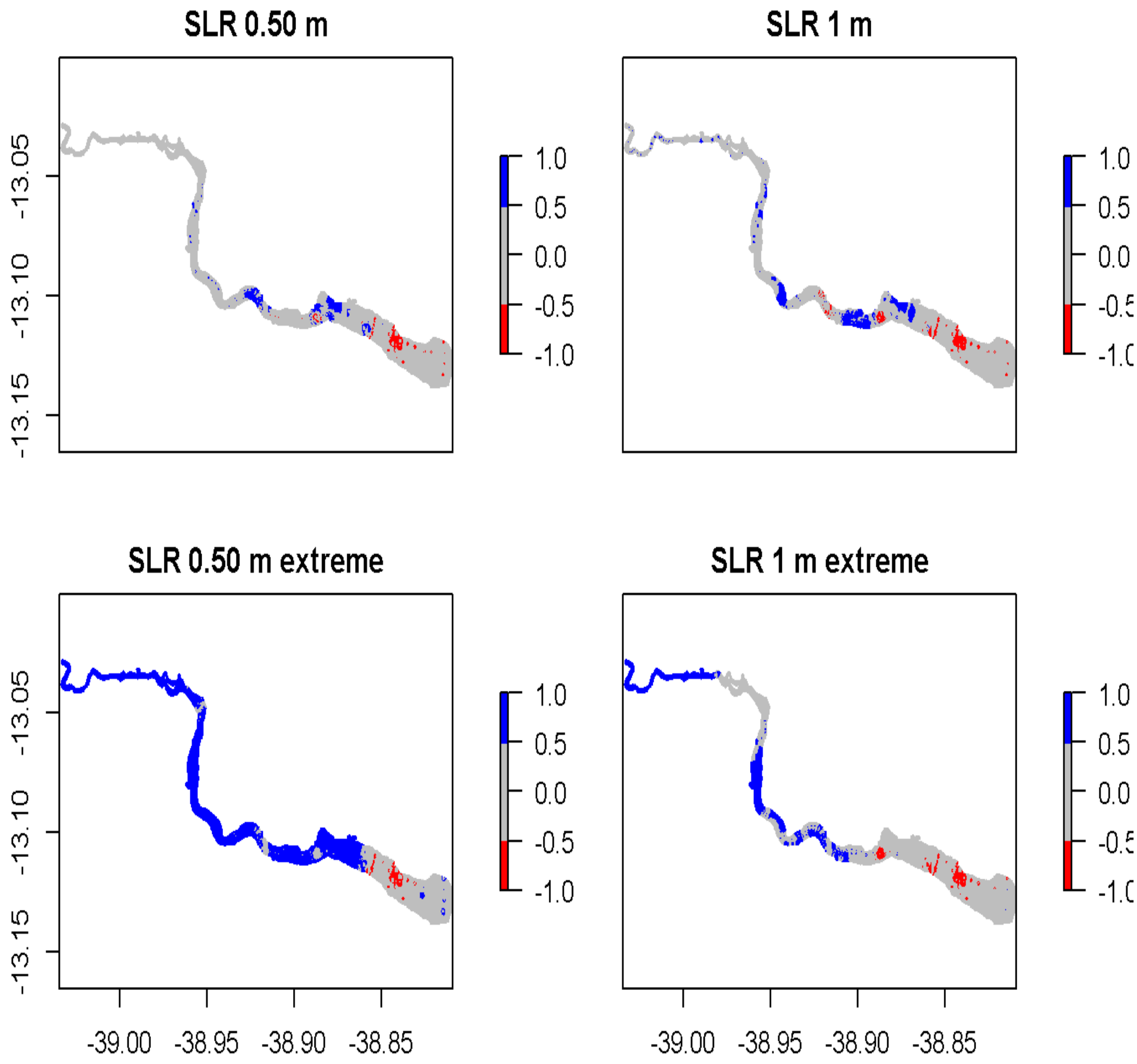
Stack changes

```
changes_Pres_Ab <- stack(ch_enf50, ch_enf1m, ch_enf50ext, ch_enf1mext)
```

Plot changes for ensemble future results (moderate and extreme scenarios)

```
plot(changes_Pres_Ab[[c(1,2,3,4)]],
     col=c('red', 'gray', 'blue'),
```

```
    main= c("SLR 0.50 m","SLR 1 m", "SLR 0.50 m extreme","SLR 1 m ext
reme"))
```



Legend

- zero indicates no changes
- 1 indicates niche expansion or colonization
- -1 indicates nicheretraction or extinction

Reference

Warren, D.L., Glor, R.E., Turelli, M., 2008. Environmental niche equivalency versus conservatism: Quantitative approaches to niche evolution. Evolution (N. Y). 62, 2868–2883. https://doi.org/10.1111/j.1558-5646.2008.00482.x

Naimi, B., Araújo, M.B., 2016. Sdm: A reproducible and extensible R platform for species distribution modelling. Ecography (Cop.). 39, 368–375. https://doi.org/10.1111/ecog.01881

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