Marine Pollution Bulletin 208 (2024) 117028

Contents lists available at ScienceDirect

Marine Pollution Bulletin

journal homepage: www.elsevier.com/locate/marpolbul

Hypoxia extreme events in a changing climate: Machine learning methods and deterministic simulations for future scenarios development in the Venice Lagoon

Federica Zennaro [a,b], Elisa Furlan [a,b], Donata Canu [c], Leslie Aveytua Alcazar [c], Ginevra Rosati [c], Cosimo Solidoro [c], Andrea Critto [a,b,*]

[a] Department of Environmental Sciences, Informatics and Statistics, Ca' Foscari University of Venice, Venice, Italy
[b] Fondazione CMCC - Centro Euro-Mediterraneo sui Cambiamenti Climatici, Italy
[c] National Institute of Oceanography and Experimental Geophysics (OGS), 34010 Trieste, Italy

A R T I C L E I N F O

Keywords:
Hypoxia
Extreme events
Future scenarios
Machine learning
Coupled hydrodynamic-biogeochemical model
Climate model

A B S T R A C T

Climate change pressures include the dissolved oxygen decline that in lagoon ecosystems can lead to hypoxia, i.e. low dissolved oxygen concentrations, which have consequences to ecosystem functioning including biogeochemical cycling from mild to severe disruption. The study investigates the potential of machine learning (ML) and deterministic models to predict future hypoxia events. Employing ML models, e.g. Random Forest and AdaBoost, past hypoxia events (2008–2019) in the Venice Lagoon were classified with an F1 score of around 0.83, based on water quality, meteorological, and spatio-temporal factors. Future scenarios (2050, 2100) were estimated by integrating hydrodynamic-biogeochemical and climate projections. Results suggest hypoxia events will increase from 3.5 % to 8.8 % by 2100, particularly in landward lagoon areas. Summer prediction foresee a rise from 118 events to 265 by 2100, with a longer hypoxia-prone season. This model is a valuable tool for developing hypoxia scenarios, aiding in identifying restoration hotspots for climate-threatened lagoons.

1. Introduction

Climate change is leading to the breaking of climate extremes (e.g., floods, heat waves, drought) long-standing records by large margins (Fisher et al., 2021). Less widely known but equally impactful and dangerous are extreme events that undermine water bodies such as marine heat waves, eutrophication, and hypoxia (Gruber et al., 2021). In this regard, hypoxia, or dissolved oxygen (DO) at low enough levels to impair organisms (Diamond et al., 2023), is one of the most dangerous and most potentially prone to increase in number and entity due to climate change (Du et al., 2018).

Hypoxia is defined in terms of measurable consequences reflected in the ecosystem, such as the oxygen concentration at which fisheries collapse (Renaud, 1986) or a particular biological function is impaired (Diaz and Rosenberg, 1995). Regarding the threshold chosen in this methodology, it is important to consider that hypoxia thresholds proposed in the literature range from 2 mgO2/l (Diaz and Rosenberg, 2008) to 4 mgO2/l (Paerl, 2006). 2 mgO2/l refers to the oxygen level for fisheries mortality, but there is ample experimental evidence that 2 mgO2/l may be insufficient to describe the onset of hypoxia for many organisms that experience hypoxic effects at higher oxygen concentrations, i.e. up to 4 mgO2/l (Pezner et al., 2023; Tellier et al., 2022; Vaquer-Sunyer and Duarte, 2008). Accordingly, 4 mgO2/l is the selected threshold within this methodology, as more representative of the ecosystem depletion.

In aquatic systems, hypoxia can commonly be attributable to natural causes such as diurnal oscillations in algal respiration, seasonal flooding, and stratification. Nevertheless, the current landscape reveals a heightened frequency and intensity of hypoxic events (Sampaio et al., 2021): this alarming trend can be traced back to diminishing oxygen concentrations (i.e., deoxygenation) that have been declining since at least the mid-20th century (Baxter, 2019). This phenomenon is one of the most critical issues in aquatic systems driven by both climate change and human activities; depending on *i*) elevated temperatures, *ii*) increased CO2 levels, *iii*) heightened nutrient inputs, and *iv*) shifts in marine species' abundance and distribution (Breitburg et al., 2018). Hypoxia puts at high risk the survival of aquatic organisms, indeed a certain level of DO concentration is essential to sustain the metabolic

* Corresponding author at: Department of Environmental Sciences, Informatics and Statistics, Ca' Foscari University of Venice, Venice, Italy.
E-mail address: critto@unive.it (A. Critto).

https://doi.org/10.1016/j.marpolbul.2024.117028
Received 9 February 2024; Received in revised form 17 September 2024; Accepted 17 September 2024
Available online 3 October 2024

and behavioural demands of aquatic life, such as oxygen uptake rate, deed activity, reproduction, respiration, and habitat selection (Justić et al., 1996). Among all the water bodies, transitional environments such as lagoons are particularly at high risk of hypoxia due to their delicate interface between land and sea. Monitoring, identifying, evaluating, and predicting hypoxia in transitional environments is a topic of high importance. Nevertheless, there is a lack of studies and methods devoted to this in the literature. Most studies focus on the evaluation of past hypoxia events and their consequences on the ecosystem (Brigolin et al., 2021; Munari and Mistri, 2011; Solidoro et al., 2010) but as for future climate change predictions, studies addressing this topic are not so widespread in the literature. The few case studies that handle future scenarios of hypoxia in coastal ecosystems have a common aspect which is the development of the scenarios using deterministic models, such as physical models rather than biogeochemical or hydro-ecological. For example, (Lehrter et al., 2017) describe the application of a coastal ocean ecosystem model to assess the effect of a future climate scenario of plus +3 °C air temperature and +10 % river discharge on hypoxia in the northern Gulf of Mexico. They applied a deterministic model that estimates a warmer and wetter future climate will, on average, worsen the extent and duration of hypoxia in the analyzed system. Or Meier et al. (2021) developed an ensemble deterministic model composed by Earth system, regional, catchment, atmospheric, and Baltic Sea ecosystem models, to investigate whether climate change will intensify hypoxia in the Baltic Sea. Their scenario simulations have suggested an expansion of the hypoxic area in a future climate of the analyzed region. Duvall et al. (2022) developed and calibrated a three-dimensional hydrodynamic model for Pensacola Bay, a shallow subtropical estuary in the northeastern Gulf of Mexico. They found that the impacts of climate change on estuarine stratification have important implications for the development of hypoxia in shallow, subtropical systems. To quantify potential changes in the frequency and duration of hypoxia near the mid-Bay channel, they compared timescales of biological production and respiration to vertical mixing.

The present work represents the first attempt to address hypoxia and climate change in the Venice Lagoon. Among all the transitional environments at risk, the Venice Lagoon is one the most exposed and vulnerable due to its fragile nature of sea-land interface, its past of anthropogenic stress and modifications, and its valuable economic, historical, social, and ecosystemic importance (Anelli Monti et al., 2021). Nowadays the Lagoon is overall well-oxygenated (Çevirgen et al., 2020), and it might be classified as a well-mixed estuary (i.e., the water column is completely mixed, making the estuary vertically homogeneous), defined by a strong inshore salinity gradient (Bendoricchio and De Boni, 2005; Solidoro et al., 2004). Nevertheless, the increase in the frequency of summer heat waves and drought due to climate change could lead to an increase of hypoxic events occurrence and extent (Brigolin et al., 2021). Indeed, during the last years, the Lagoon has faced several hypoxic crises (Facca et al., 2014; Brigolin et al., 2021) that often resulted in mass fish and benthic invertebrate mortalities (Vaquer-Sunyer and Duarte, 2008). Moreover, it has to be considered that the local climate adaptation strategy for protecting the Lagoon and the city from sea levels in this area (Zanchettin et al., 2020) could exacerbate hypoxia events in the future. Indeed, in recent years, increasing sea levels have prompted the construction of the mobile barriers (MOSE project) to protect the city of Venice from high tides and storm surges (CVN, 1997). The MOSE project aims to defend the city from inundations by blocking water inflows at the Lagoon inlets when the sea level rises beyond a certain threshold. In this regard, considerable can be side effects on WQ and on the entire Lagoon ecosystem caused by the interrupted water circulation (i.e. prolonged residence time). In fact, as the barriers are expected to be continuously closed for very long tidal periods (more days) due to sea level rise and extreme storms, very low DO concentrations and other harmful effects are likely to occur in a more massive way (Umgiesser, 2020; Melaku Canu et al., 2001; Leoni et al., 2022).

In this context, this paper aims at developing a reliable method able to disentangle emerging patterns from the complex interactions between hypoxia events, water quality (WQ) and climate drivers, and to predict their future patterns in order to obtain robust hypoxia scenarios under future climate change conditions. As for all extreme events, detecting hypoxias that represent a small part of events in large datasets is a major challenge, precisely because of their nature of infrequent events. The more updated and resolute biogeochemical model for the Venice Lagoon, named SHYFEM-BFM model (Canu et al., 2023), provides the daily average of various biogeochemical variables including DO. However, as the majority of deterministic models, it has a limited capability to capture the entire range of natural variability reproducing fluctuations and extremes, especially when biological dynamics are involved (Kwiatkowski et al., 2020) due to: i) the inherent assumption and simplification adopted to represent all components of the system considered to be relevant for capturing the main system features and is therefore, by design, ineffective to reproduce all fluctuations and extremes. Furthermore, the model's capability to reproduce extreme events is reduced by the lack of high variability in the external forcings (i.e., rivers input), which is filtered off by the (low) frequency of the forcing monitoring systems (Zennaro et al., 2023). For this reason, in this methodology it is chosen to combine the deterministic model with the emerging Machine Learning (ML) approach, including various algorithms such as Random Forest (RF), AdaBoost, XG Boost, Multi-Layer Perceptron (MLP), Logistic Regression (LR) and Weighted Support Vector Machine (SVM) as well as their ensemble versions using the Stacking ensemble technique. The objective is to test their capacity to provide accurate analysis on an imbalanced dataset, such as that of hypoxia events versus normal conditions. This decision leverages recent advancements in ML, that has strong predictive capabilities and capitalizes on the synergies between these capabilities and the strengths of deterministic simulations. Indeed, recent advances in the modeling of oxygen depletion, show that ML have provided valuable insights into the impacts of climate change and human activities on aquatic ecosystems. Several pioneering studies have explored innovative methods for predicting DO dynamics. Yu et al. (2020) introduced a model combining empirical orthogonal functions and neural networks to track DO changes, while Liang et al. (2023) integrated spatiotemporal characteristics to enhance forecasting capabilities. Additionally, Pezner et al. (2023) investigated future hypoxia on coral reefs under climate change scenarios.

In this paper specifically, the methodology attempts to improve the evaluation of oxygen depletion events in the Venice Lagoon over ten years (2008–2019) and the prediction of potential changes in the mid (2050) and far (2100) future, under the Representative Concentration Pathways (RCP) 8.5 scenario (Intergovernmental Panel on Climate Change, 2014; Riahi et al., 2011), chosen as in line with the current trajectory of emissions and with the pathway promoted by policymakers championing the use of fossil fuels such as coal-fired power. The process involves the ML models fine-tuning (training, validating and testing) using a suite of biogeochemical and meteorological (i.e. the variables that can infer deviations in the triggering of hypoxias dynamics, e.g. strong solar radiation and meteorological drought (Beck and Bruland, 2000; Cladas et al., 2016; Pérez-Ruzafa et al., 2019; Xu et al., 2021)) response variables to classify extreme hypoxia events.

Building on this methodology, this study may be useful in developing of reliable hypoxia scenarios for alarming these extreme events and, ultimately, be effective for the management of the lagoon, thus pursuing the EU Mission Starfish 2030 (European Commission, Directorate-General for Research and Innovation, Lamy et al., 2020) goals. Indeed, the Mission proposes to address hypoxia with specific targets and actions to regenerate marine and coastal ecosystems by 2030. The method advanced here is envisioned to be a prototype of future digital twins used by stakeholder groups, such as the aquaculture industry, managing the risk of hypoxia potentially killing their farmed organisms, and observational scientists, aiming to expand their observed data to new variables.

In the next sections, after a brief description of the case study (Section 2), the datasets and methodological approach underpinning the extreme event modeling are explained (Section 3). Finally, the results of future climate change hypoxia event scenarios are presented (Section 4) and discussed (Section 5).

2. Study area

Venice Lagoon is located in the northern part of the Adriatic Sea (location 45°N, 12°E), it is the largest transitional environment of the Mediterranean Sea (Fig. 1). The Lagoon is a very polymorphous environment and it hosts abundant fauna and flora that are of relevant natural and socioeconomic importance (Bon et al., 2001). It is a shallow coastal ecosystem covering an area of about 550 Km^2, of which nearly 400 km^2 characterized by open waters, and the remaining part by extensive fish farms (locally called “valli da pesca”) where the water circulation and the fish species movement is controlled (Anelli Monti et al., 2021). Its hydrodynamic regime is dominated by the tide. It exchanges around 385 × 106 m^3 of water per day with the sea, through three inlets (Lido, Malamocco and Chioggia), and it is crossed by a network of channels, which for the most part are shallower than 2 m (Melaku Canu et al., 2001). The Lagoon exhibits a mean depth of ca. 1.0–1.2 m, but in the main channels and inlets depth ranges between 10 and 20 m with an exception in the Malamocco inlet which is the deepest site of the northern Adriatic Sea (ca. 50 m). The tidal sea-water exchange through three inlets is approximately 1.46×10^9 m^3 at each tidal cycle (12h), which is more than half of the entire water loading, although the water renewal in the inner areas may take ca. 10–20 days (Sfriso et al., 2009). The system of mobile gates (MOSE), designed and built to protect the historical town from the effects of high tides, was recently completed (2020). This system allows one to disconnect the Lagoon from the open sea in case of forecasted high tide, maintaining a lower level of water inside the lagoon. (Anelli Monti et al., 2021; Çevirgen et al., 2020; Bendoricchio and De Boni, 2005; Solidoro et al., 2004; Facca et al., 2014; Sfriso and Facca, 2007; Brigolin et al., 2021; Vaquer-Sunyer and Duarte, 2008; Umgiesser, 2020; Melaku Canu et al., 2001).

As a result of hydrodynamic and morphological heterogeneity, accompanied by differences in the proximity of water bodies to anthropogenic pressures, there is high spatial variability in the WQ of the Lagoon, such as salinity gradients (Solidoro et al., 2004), concentration of nutrients and Chl-a (Berti et al., 2022; Facca et al., 2014; Micheletti et al., 2011; Solidoro et al., 2004). For example, Facca et al. (2014) observed a clear gradient in total nitrogen between the northern and southern Lagoon, with decreasing concentrations seaward and higher concentrations of total phosphorous, total carbon, and inorganic carbon in the central basin. Similarly, Solidoro et al. (2004) reported high nutrient and Chl-a concentrations in the central Lagoon, with less bloom in areas with greater sea influence. In general, higher concentrations of nutrients and other contaminants are found in areas close to urban canals (e.g. Venice city center), industrial canals affected by effluents, confined areas with limited hydrodynamics (longer residence time) and landward areas affected by tributary discharges, fish farm outfalls and runoff from the mainland (e.g. Berti et al., 2022). As the landward areas of the Lagoon receive most of the inputs from the catchment, higher concentrations of pollutants exceeding the environmental quality standards (DM 23/04/1998, DM 367/2003) were also found there by Micheletti et al. (2011).

In response to changes caused by multiple pressures (Solidoro et al., 2010) the Venice Lagoon is continuously evolving. In addition to the intensive anthropogenic activities in and around the Lagoon, the prevalence of several climate-related pressures in the area, and in the Mediterranean region in general, may alter the water quality and ecological status of the Lagoon. For example, climate-related pressures prevalent in the region include variations in precipitation and consequent river flooding (e.g. Pesce et al., 2018), variations in wind regimes (Solidoro et al., 2010), storm events (Lionello et al., 2021), as well as drought in the Mediterranean region (Tramblay et al., 2020). These hazards can lead to the alteration of the hydro-morphodynamic processes that determine the WQ of the lagoon. In particular, they can affect the release, transport and redistribution of nutrients and/or pollutants, and alter WQ parameters such as temperature, salinity, turbidity, pH, and DO, with consequent effects on primary productivity and higher trophic levels.

3. Data and methods

This paper presents a novel modeling methodology that aims to study trends in past hypoxia events (2008–2019) and to estimate potential changes in their occurrence due to climate change in the mid and far future (2050 and 2100 scenarios). The research is based on historical onsite monitored data and future projections, and consists in the development of a multiple machine learning, hydrodynamic, biogeochemical and climate model, herein ML-BGC&Climate, aimed at estimating extreme oxygen depletion as defined by the specific threshold (Section 3.3). The methodology (Fig. 2) follows two consecutive phases: first, the binary classification of *hypoxia events* or *normal conditions* using a set of ML algorithms and their Staked ensemble version trained on historical data; second, the integration of the selection and application of *multiple ML models* with the projections of the deterministic hydrodynamic-biogeochemical and climatemodels. Here, the selection of the multiple MLs is based on the MLs performances on the test set and the multiple models aim to reduce the uncertainties in the predictions associated with the use of a single model.

The following sections report the datasets and variables implicated (Sections 3.1 and 3.2) in the study. Additionally, it offers a detailed description of the methodology, starting from the hypoxia threshold employed (Section 3.3), and an in-depth explanation of the multiple ML-BGC&Climate model development, by describing the ML models (Section 3.4) and the hypoxia scenarios (Section 3.5) design.

3.1. Features selections and historical data

3.1.1. Input variables

The choice of the input variables for the ML models are connected to the processes driving oxygen depletion. The oxygen cycle is driven by a network of biological, physical, and meteorological processes, whose imbalances may lead to hypoxic conditions, causing large-scale damage to aquatic life (Pena et al., 2010; Oschlies et al., 2018). In particular: *i*) surface water oxygen concentrations are substantially influenced by air-sea gas exchange, dependent on the gas saturation levels and water turbulence, both affected by temperature, as well as *ii*) oxygen production through photosynthesis by phytoplankton macroalgae, and macrophytes, and *iii*) oxygen sinks through the collective respiration by all the living marine species. In the deeper part of the water column, oxygen concentrations are impacted by *iv*) vertical transport, which depends on the levels of vertical mixing and the pycnocline, and *v*) respiration, especially by microbes remineralizing non-living organic matter at the bottom, or in the sediments. Finally, as most biogeochemical tracers, oxygen is also influenced by *vi*) water advection, and *vii*) diffusion processes. Accordingly, even response variables related to hypoxia events were selected (Table 1) among the available WQ and meteorological data, including DO (mmol/m^3), water temperature (°C), salinity (PSU), chlorophyll-a (Chl-a, μg/L), precipitation (mm), solar radiation (W/m^3) and relative humidity (%).

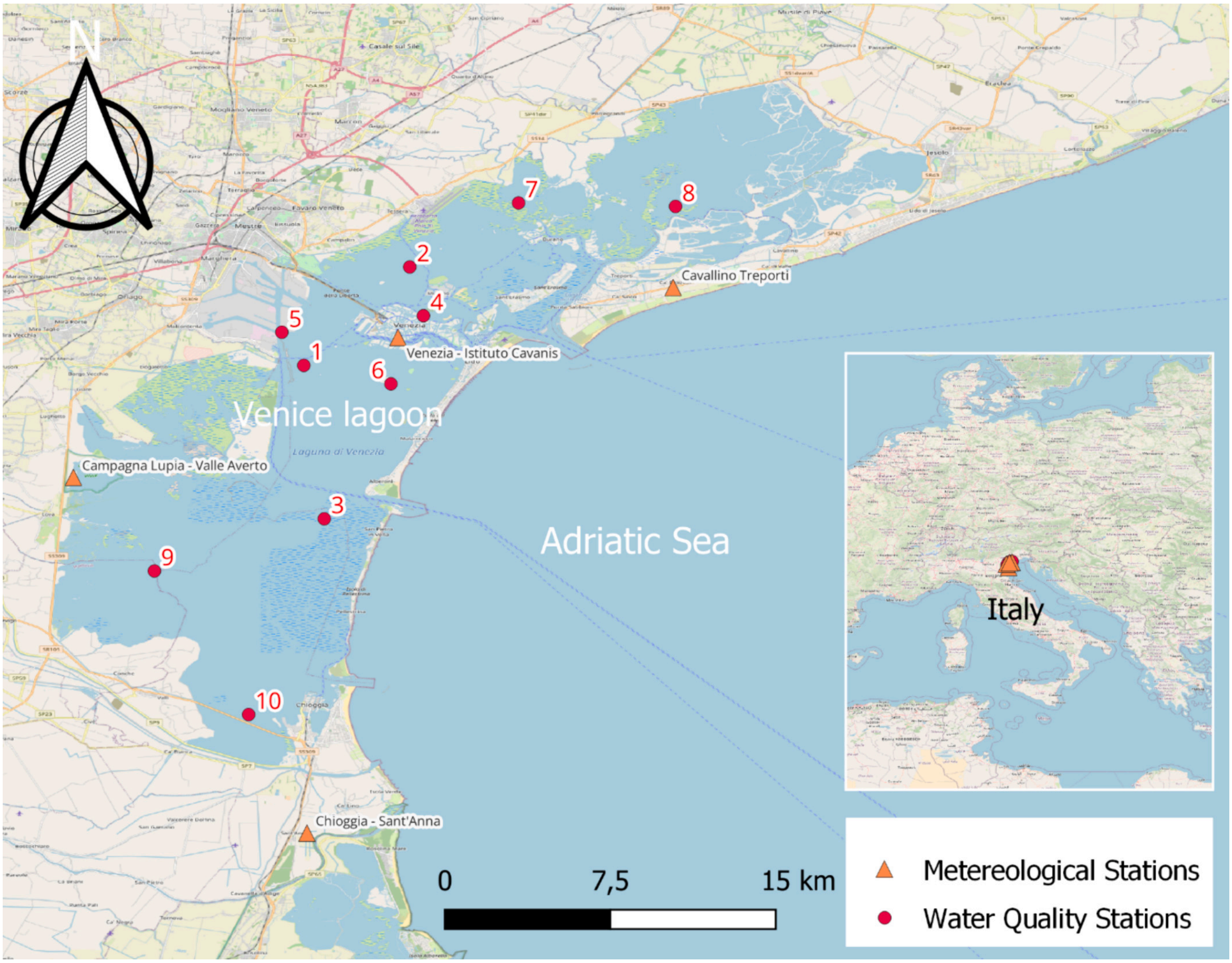

Fig. 1. Map showing the 10 sampling probes sites investigated (red dots) within the Venice Lagoon case study and the 4 meteorological stations (orange triangles). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

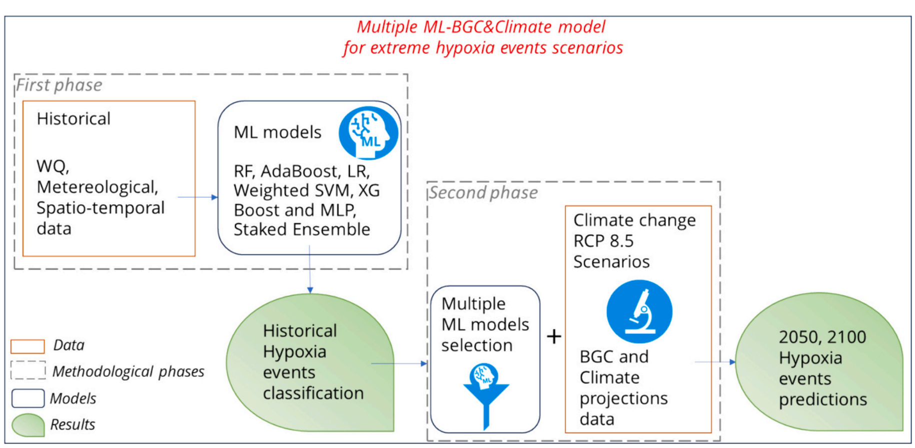

Fig. 2. Overall methodology behind hypoxia extreme events analysis and predictions.

Table 1
Variables used as input in the ML models and general statistics of the historical period (2008–2019).

Variables	Type	Temporal resolution	Source	2008–2019	
				Range	Mean
DO (mmol/m^3)	WQ	Daily mean, 3 days cumulative	SAMANET	0.00–671.95	263.30
water temperature (°C)	WQ	Daily mean, 3 days cumulative	SAMANET	−1.55–32.24	16.66
salinity (PSU)	WQ	Daily mean, 3 days cumulative	SAMANET	1.85–37.62	29.25
Chl-a (μg/L)	WQ	Daily mean, 3 days cumulative	SAMANET	0.02–60.93	2.43
precipitation (mm)	Climate	Daily mean, 3 days cumulative	ARPAV	0.00–159.82	2.27
solar radiation (W/m^3)	Climate	Daily mean, 3 days cumulative	ARPAV	0.00–823.34	160.22
relative humidity (%)	Climate	Daily mean, 3 days cumulative	ARPAV	12.79–100.00	77.58

3.1.2. Historical time series and training dataset

The time series dataset is collected on a daily basis in the period between January 2008 and December 2019. The dataset comprises variables from two sources: *1*) WQ data from the 10 SAMANET[1] stations located at a depth of 1 m managed by Provveditorato for the Public Works of Veneto, Trentino Alto Adige, and Friuli Venezia Giulia (PROVVV.OO.PP). *2*) Meteorological data from 4 stations located across the Venice Lagoon, provided by the Regional Agency for Environmental Prevention and Protection of Veneto (ARPAV). Since the spatial distribution of meteorological stations does not match all ten WQ stations (refer to Fig. 1), they have been interpolated using the Inverse Distance Weighting (IDW) method. All the features are aligned as a daily mean, except precipitation, which is presented as daily cumulative precipitation.

3.1.3. Time lag approach

As the occurrence of *hypoxic events* is not an instantaneous process, the indicators representing cumulatively the previous three days are calculated from daily variables. Indeed, *hypoxia events* at a given time may be partially defined by environmental conditions in previous time periods (Lee et al., 2013); and the concept of time lag has been previously adopted in ML modeling for predicting DO (Politikos et al., 2021; Khani and Rajaee, 2017; Yu et al., 2020). Accordingly, within present methodology both the daily variables and their three-day cumulative indicator for each variable are taken into account, and the more influencing ones are chosen, (in Section 3.4 the indicators selection procedure is explained).

3.2. Future WQ and climate projections

The development of climate change scenarios is based on projections from two models, respectively the SHYFEM-BFM for the WQ variables and the COSMO-CLM for the meteorological variables (Table 2). Both these two deterministic models are forced with the RCP 8.5 business-as-usual scenario and provide, as output, the projections until the far future (2100). The reason beyond the choice of the RCP8.5 scenario for the 5th IPCC report instead of the SSP5-8.5 scenario of the 6th IPCC report is related to 1) CMIP6 data to build the Lagoon forcing and boundary conditions at the proper spatial scale are not available since downscaled biogeochemical and meteorological dynamic are not yet available. 2) CMIP6 highlighted a remarkable inter-model disagreement, which can exceed scenario uncertainty, on the projected evolution of DO and other ocean biogeochemical variables (Kwiatkowski et al., 2020).

3.2.1. Atmospheric model

COSMO Climate Change (COSMO-CLM) model, i.e., Consortium for Small-scale Modeling - Climate Limited-area Modeling (Rockel and Geyer, 2008), provides projections of future precipitation, relative humidity, and solar radiation at the regional level. It is the climate version of the COSMO LM model (Steppeler et al., 2003), which is the operational non-hydrostatic mesoscale weather forecast model developed initially by the German Weather Service (DWD) and then by the European Consortium COSMO. COSMO-CLM is currently used to perform dynamical downscaling of global climate simulations. For the case study scale, the COSMO-CLM model reports the predictions for the time period 2006–2100 covering the Venice Lagoon with a spatial resolution of 8 km for the RCP 8.5 scenario (Bucchignani et al., 2016; Zollo et al., 2016).

3.2.2. Hydrodynamical-biogeochemical model

The hydrodynamic-biogeochemical model SHYFEM-BFM has been recently developed and applied to the Venice Lagoon (Melaku Canu et al., 2023), compared with field data, and used to perform simulations under climate scenarios. The coupled model is based on the open-source models, Shallow water HYdrodynamic Finite Element Model (SHYFEM) for the hydrodynamic (Umgiesser et al., 2004), and on Biogeochemical Flux Model (BFM) for the biogeochemistry (Vichi et al., 2020). The BFM is a biomass-based numerical model designed to simulate key biogeochemical processes in marine ecosystem. It tracks the cycles of nutrients, carbon, oxygen, a pool of phytoplankton, zooplankton and bacteria across the modeled system.

The SHYFEM-BFM model is implemented using an unstructured mesh of over 10,000 elements and 6000 node that allows for a good representation of the lagoon properties and variability. It takes into account time variable inputs, boundary conditions and meteorological forcing such as river inputs of water and nutrients, exchange of water and biogeochemical variables with the sea, and meteorological forcing. The SHYFEM-BFM model is forced using the best available and coherent information to perform the Venice Lagoon biogeochemical climate scenario. The meteorological conditions are provided by the COSMO-CLM model covering the Venice Lagoon with a spatial resolution of 8 km (Bucchignani et al., 2016; Zollo et al., 2016), and the marine biogeochemical boundary conditions are provided by the climate simulations for the years 2005–2100 performed for the whole Mediterranean Sea with the OGSTM-BFM (Ocean General Circulation Model with Biogeochemical Flux Model) biogeochemical model (Reale et al., 2022) which dynamically simulates the Mediterranean Sea biogeochemistry at 1/16° spatial resolution, ~6.5 km, with 72 unevenly spaced vertical levels (ranging from 3 m at the surface down to 600 m in the deeper layers; see Lovato et al., 2013) (the list of acronyms is reported in SM1). Marine water levels at the inlets were estimated from (Zanchettin et al., 2021), applying a linear trend up to the projected value of 0.71 m at the end of the century (for the 8.5 RCP scenario, using the 50° percentile of the ensemble model projections). The model simulates heat transport, water temperature, and oxygen concentration, and all the biogeochemical variables, including Chlorophyll, at each node of the high-resolution domain, at each day of simulation, in response of the changing meteorological forcing and boundary conditions.

3.2.3. DO bias correction

In this study, all future projections are incorporated into the ML model as proper values derived from the hydrodynamic-biogeochemical and climate models exception DO. The reason for this exception is the

[1] SAMANET (Advanced Environmental Monitoring System of the Venice Lagoon) acquires 30 min of WQ data every day, providing valuable insights into the evolution of the lagoon ecosystem.

Table 2
Hydrodynamic-biogeochemical and climate projections obtained from the deterministic models. *Rescaled DO future projections aligned with historical values.

Variables	Source	2019		2050		2100	
		Range	Mean	Range	Mean	Range	Mean
DO (mmol/m^3)	SHYFEM-BFM	190.86–342.01	258.02	182.33–556.48 *60.29–452.32	265.20 *246.90	168.71–511.97 *49.69–410.63	243.37 *222.03
Water temperature (°C)	SHYFEM-BFM	2.38–32.88	16.83	4.06–34.01	19.65	8.83–38.98	22.69
Salinity (PSU)	SHYFEM-BFM	21.38–36.71	31.38	24.86–37.27	32.85	25.49–38.47	33.64
Chl-a (μg/L)	SHYFEM-BFM	0.30–6.93	1.41	0.09–13.27	1.20	0.05–7.43	1.00
Precipitation (mm)	COSMO-CLM	0.00–40.30	0.97	0.00–35.42	0.91	0.00–27.84	1.11
Solar radiation (W/m^3)	COSMO-CLM	2.28–294.30	132.11	2.16–294.71	132.19	1.78–290.03	133.46
Relative humidity (%)	COSMO-CLM	34.72–97.27	72.59	35.13–94.78	72.17	23.69–96.67	68.42

bias between model and observation in the historical data. Specifically, the DO min-max range of the 2019 baseline extends from 190.86 to 342.01 mmol/m^3. In contrast, the DO min-max range of the historical data spans from 0.00 to 671.95 mmol/m^3 (see Tables 1 and 2). This disparity has necessitated the recalculation of the DO variable to ensure its alignment with historical trends. In order to align the mid and far future time series with the historical ones, a three-step process is implemented: first, for each station (1–10) and for each calendar day the 20° percentile in the historical timeframe (2008–2019) is extracted. The 20° percentile of the historical observations has been selected as it is the indicator that best represents the historical percentage of oxygen depletion events (3.13 %) among a set of other indicators tried (e.g. mean, minimum, 10° and 30° percentiles). Thus, 10 vectors of 365 elements are calculated, each corresponding to the daily 20° percentile for each station in the historical period, named here *reference*. Secondly, the *model anomalies* are computed from output of the SHYFEM-BFM simulations as the difference of the DO values between the years 2050 and 2019 (*mid future anomalies*) and between 2100 and 2019 (*far future anomalies*) for each station and calendar day. Finally, the *mid future anomalies* and the *far future anomalies* are summed up to the *reference* to obtain the corrected DO data for the mid and far future scenarios.

3.3. Hypoxia events threshold: the extreme event duration

Concerning the events duration, the *hypoxia event* is here specifically defined as the occurrence wherein the DO concentration remains below the established limit of 125 mmol/m^3 (equivalent to 4 mgO2/l) (Paerl, 2006; Politikos et al., 2021)) for a duration of at least 8 h within a single day even if not continuous (e.g. DO < 125 mmol/m^3 from 00:00 to 05:00 am and from 08:00 am to 11:00 am of a given day). Furthermore, in order to account for situations where data are missing for specific days, a proportion equivalent to 8/24, i.e. the 33.3 %, of the total hours in which the DO concentrations stay within the predefined threshold level is taken into consideration. This approach aims to compensate for data gaps, without having to remove days with missing data from the dataset, thus avoiding its reduction. This systematic approach ensures consistent identification and accurate characterization of *hypoxia events*, even in scenarios with incomplete data coverage. Consideration of events duration is extremely relevant in the case study because as defined by Tellier et al. (2022) *diel hypoxia* is a natural phenomenon that can develop in highly productive, shallow, aquatic habitats, such the Venice Lagoon is, during the warmer months. Its occurrence is common in wetlands and estuaries driven by the interaction between variable rates of primary production and consistently high respiration-induced oxygen demand (Cheek et al., 2009). During the day, high levels of photosynthesis effectively compensate for the oxygen consumed through respiration. However, as photosynthesis ceases at night, the high biological oxygen demand rapidly reduces DO concentrations to low levels, and atmospheric diffusion cannot adequately keep pace with demand. DO levels are subsequently restored the following day when photosynthesis resumes. The warm temperatures experienced in shallow waters limit oxygen solubility and favor seasonal stratification, enhancing deoxygenation. The rates of oxygen consumption and renewal in these shallow, isolated systems are in such a delicate balance that the nocturnal cessation of photosynthesis results in decreased DO within hours of sunset (Cornell and Klarer, 2008). Accordingly, a descriptive analysis of the historical hypoxia events within 2008 and 2019 in the Venice Lagoon is reported in Section 4.1.

3.4. ML models and skill metrics

Understanding and predicting extreme events and their associated anomalous statistics is a major challenge in complex natural systems (Qi and Majda, 2022). ML provides a useful tool to learn the essential dynamics directly from data. Indeed, ML models are well suited to problems with various interactions between inputs and outputs being able to disentangle complex non-linear relationships between variables. The choice of the present methodology is related to the considerations on the available water quality and meteorological datasets. Datasets that are characterized by high complexity and non-linear distribution and by a short available timeframe, i.e. 2008–2019 (historical) and 2050, 2100 (future). In this case, applying statistical methods for the modeling of extreme events, for example, a non-stationary methodology based on a generalized Pareto distribution, could be useful in highlighting seasonality, trends, and cycles. However, the main goal, here, is to understand the relationships between the variables involved and hypoxic events in order to learn the conditions that trigger a hypoxic event. Once these conditions are understood from past data, they can be applied to future scenarios where trends and cycles may be different due to climate change. This approach allows for estimates related to climate change, considering that future trends and cycles might vary. The evolution theory approach, on the contrary, assumes that historical trends will continue into the future, which is not necessarily true and may produce unrealistic results (see, e.g., Luke et al., 2017; Serinaldi et al., 2018; Serinaldi and Kilsby, 2015). The reliability of the nonstationary approach requires relating the time-varying behavior to the underlying cause-and-effect processes that generate it (Serinaldi and Kilsby, 2015), which cannot be obtained from statistical approaches.

3.4.1. Unbalanced datasets

ML techniques have undergone a significant revolution in the last two decades owing to the availability of unprecedented volumes of training data in many domains and the considerable progress in computer hardware (e.g., Sonnewald et al. (2021)). Due to their power, ML models can be an ideal tool for classify *hypoxia events*, but since extreme events are characterized by an unbalanced dataset, this method can face some issues. An unbalanced dataset represents a particular challenge in classification problems, where the uneven distribution between classes makes accurate data classification difficult. This implies that whether a dataset is biased towards one class, an algorithm trained on the same data will be biased towards the same class. The model learns more from the biased examples than from the examples in the minority class. The outcome could be a scenario where the model assumes that all the data belongs to the majority class. As a result, the model will appear naive in its predictions, regardless of the high accuracy it achieves.

Accordingly with the complexity of *hypoxia events* unbalanced dataset (~3:100 ratio), an ensemble-based strategy is used to ensure the robustness of the analyses. The latest advances in ML algorithms and tools are applied to effectively transform the large amount of data into useful information and knowledge. Therefore, multiple ML models are proposed to predict the *hypoxia extreme events* that occur in the complex Venice Lagoon system. Among all the response variables involved (comprehensive of daily mean and time-lagged indicators), the most influential indicators are selected through ML future importance, by applying permutation importance and the Gini index. Accordingly with the feature importance procedure, the final set of response variables comprehend: daily DO, water temperature, and precipitation, and 3 cumulative days Chl-a, salinity, solar radiation and humidity (in SM2 more details are reported).

3.4.2. ML models ensemble and staking ensemble technique

The MLs task involves the binary classification of the *hypoxia event* (class 0) versus the normal condition (class 1) of each day of the historical period. The multiple approach combines the performance and results of many classifiers to improve the performance of a single classifier and try to achieve the highest possible prediction accuracy in the final model. The multiple ML modeling is intended here in the training of six separate well-known ML models: Random Forest (RF) (Liaw and Wiener, 2002), AdaBoost (Freund and Schapire, 1997), Linear Regression (LR) (Bisong, 2019), Weighted Support Vector Machine (SVM), XG Boost (Chen and Guestrin, 2016) and Multi-Layer Perceptron (MLP) (Ahmed et al., 2019). In addition the Staking ensemble technique is used to test whether multiple learning methods are more effective than a single one. In SM3 an insight with the characteristics of each algorithm is reported.

Each proposed algorithm is fine-tuned in the present methodology using the most suited settings to weight the classes (e.g. *class_weight*). In contrast to single algorithms, the design of the Staking ensemble is more complex. Stacking is an ensemble learning technique to combine multiple classification models via a meta-classifier. The individual classification models, here RF, AdaBoost, LR and SVM, are trained based on the complete training set; then, the meta-classifier (i.e. LR) is fitted based on the outputs - meta-features - of the individual classification models in the ensemble (in SM4 the architecture of the Stacking ensemble is reported).

3.4.3. Training and validation

All the presented algorithms are validated with the cross-validation technique, necessary to assess models' performance and generalizability. This technique involves dividing a dataset into subsets, typically a training set and a validation set, with multiple iterations. In k-fold cross-validation, the data is divided into 'k' equal parts, and the model is trained and tested 'k' times, with each part serving as the validation set once. This process helps to detect overfitting, as the model's performance is evaluated on multiple, non-overlapping data subsets. Cross-validation provides a more reliable estimate of a model's performance than a single train-test split, making it an essential tool for model selection and hyperparameter tuning (Pedregosa et al., 2011).

Finally, to evaluate the predictive performance of the multiple ML algorithms on the testing set, the accuracy, ROC-AUC are reported. Accuracy is a common performance metric in ML, representing the ratio of correctly predicted instances to the total number of instances in a dataset. It provides a straightforward measure of the overall correctness of a model, making it easy to interpret. However, accuracy can be misleading when dealing with unbalanced datasets, where one class dominates the other, as the model may achieve high accuracy simply by predicting the majority class (Baldi et al., 2000). In such cases, Receiver Operating Characteristic-Area Under the Curve (ROC-AUC) is a valuable alternative metric. ROC-AUC quantifies a model's ability to discriminate between positive and negative classes at different probability thresholds, providing a more comprehensive assessment of classification performance, especially when class imbalances are present. It measures the area under the ROC curve, with a value of 0.5 indicating random performance and 1.0 representing perfect discrimination. A higher ROC-AUC score generally indicates a better classifier, providing a more nuanced assessment of model performance compared to accuracy. Thus, for evaluate the performances of each class precision, recall and F1 score are calculated. Precision measures the proportion of correct predictions out of the total predictions of the class, while recall measures the proportion of instances of a class that are correctly retrieved by the classifier. The F1 score is the harmonic mean of precision and recall and can be computed for each class separately or as an average over all classes (Pedregosa et al., 2011). In addition, the confusion matrices, which indicate the number of hypoxic days correctly (true positives, TP) and incorrectly (false positives, FP) identified, as well as the number of normal days correctly (true negatives, TN) and incorrectly (false negatives, FN) identified, are evaluated (Haghighi et al., 2018). Moreover, uncertainty analysis to ensure a full understanding of the results is performed through sensitivity analysis. This method permit to understand how variations in the input data affect the predictions of the model. This type of analysis is useful for identifying the most influential features and providing a greater explainability of the results evaluating the robustness and precision of the models and analyzing the contributions of the considered variables to the outcomes. Accordingly, a sensitivity analysis using the Morris method was performed (Morris, 1991).

3.5. Future climate change scenarios design

After selecting the suit of ML models that best perform on the test sets (Section 3.4), the ML-BGC&Climate model is implemented. This process implies integrating in the ML models the reference (20° percentile of the historical period 2008–2019) data and future (2050 and 2100) hydrodynamic-biogeochemical and climateprojections. As presented in the dataset section (3.2), the projections are estimated by SHYFEM-BFM model for water temperature, DO, Chl-a, salinity, and by COSMO-CLM for solar radiation, humidity, and precipitation variables.

The results consist of daily *hypoxia event* predictions and relative model uncertainty for the years 2050 and 2100, as well as for the reference period. In order to present as robust scenarios as possible, the calculation of the number of *hypoxia events* is based on the average values obtained from the results of the *multiple ML model selection* (i.e. the average of the Adaboost, RF and Staked ensemble predictions). Furthermore, estimated variability of the possible min-max prediction of the whole range of selected models is given to express the uncertainty.

An in-depth seasonal analysis (i.e. winter, spring, summer and autumn) is also carried out with a focus on summer (i.e. June, July and August) temporal variability. Furthermore, a station-based analysis is undertaken, accounting for the geographical locations of monitoring stations (Fig. 1), thereby incorporating the spatial dimension.

The model is designed to furnish daily estimates of normal and hypoxic days. As discussed in Section 4.3, the findings are presented through visual plots, facilitating a clear visualization of potential shifts in the current scenario (reference) and future scenarios (mid, and far future). These visualizations extend across the temporal dimensions of the seasons and the spatial dimensions defined by the monitoring station locations.

4. Results

4.1. Historical hypoxia events analysis

Here, an in-deep analysis of historical *hypoxia events* in the Venice Lagoon for the period 2008–2019 period is provided to understand whether past events were *diel hypoxia*, as defined by Tellier et al. (2022) or more prolonged extreme events for the Venice Lagoon. Looking at the events classified as *hypoxia* (given the threshold defined in Section 3.3) from the onsite monitored data (see Section 3.1), it is evidenced that only the 16 % of *hypoxia events* ended before the 10:00 am while the remaining 84 % continued during the daytime. These results indicate that the great majority of events are not natural temporary hypoxias but effectively dangerous events. Considering spatial variability, the stations in which more events occurred are 1, 5, 7 and 10, which are also the landward stations where the residence time of the water is higher (ca. 20 days) (Cucco and Umgiesser, 2006) (in SM5 the pie chat and the bar plots indicating the percentage and number of occurred events by station are reported).

A further explanatory analysis of *hypoxia events* characteristics shows that, when looking at the DO daily mean, a significant proportion, 40 %, of the recorded events remain within the established threshold of 125 mmol/m^3 (Fig. 3.a). This emphasizes that there is a high frequency of events that are either more intense, e.g. with very low hourly DO peaks, or that have a duration of >8 h. Then, looking at the duration of the *events* (Fig. 3.b) it is noteworthy that a substantial portion, 45 %, of the investigated events display durations that extend beyond 12 h in a day. This prolonged temporal extent of *events* highlights the persistence of hypoxic conditions below the 125 mmol/m^3 threshold for a time span that can threaten the wellness and survival of sessile organisms, unable to move towards better-oxygenated water. Finally, the duration of the *events* compared with the daily DO mean values (Fig. 3.c) shows that the longer the events, the lower the DO mean is. When the *event* lasts longer than 16 h, the daily average is always below the 125 mmol/m^3.

4.2. ML models performances

The binary classification of *hypoxia events* or *normal conditions* are performed by six separate ML models, i.e., RF, AdaBoost, LR, Weighted SVM, XG Boost, and MLP, and a Staking ensemble model. The models are trained, validated and tested with daily WQ and meteorological data monitored in the Venice Lagoon during the period 2008–2019. Their accuracy, ROC-AUC score, precision, recall, and F1 score metrics calculated on the two classes, are presented in Table 3.

The results indicate that RF, AdaBoost, MLP, and the Stacking ensemble models achieve the highest accuracy (0.99). Among them, RF, AdaBoost, and the Stacking ensemble also demonstrate the highest F1

Table 3
Performances on the test set of the ML models implemented in the methodology. The best results are evidenced in **bold**.

Algorithm	Accuracy	ROC AUC score	Class	Precision	Recall	F1 score
RF	**0.99**	0.89	0	0.88	0.78	**0.83**
			1	0.99	1.00	0.99
AdaBoost	**0.99**	0.89	0	0.87	0.79	**0.83**
			1	0.99	1.00	0.99
LR	0.93	0.93	0	0.29	**0.92**	0.45
			1	**1.00**	0.93	0.96
Weighted SVM	0.94	**0.94**	0	0.34	0.95	0.50
			1	**1.00**	0.94	0.97
XG Boost	0.98	**0.94**	0	0.67	0.89	0.76
			1	**1.00**	0.99	0.99
MLP	**0.99**	0.80	0	**0.94**	0.61	0.74
			1	0.99	1.00	0.99
Staking ensemble	**0.99**	0.89	0	0.91	0.78	**0.84**
			1	0.99	1.00	1.00

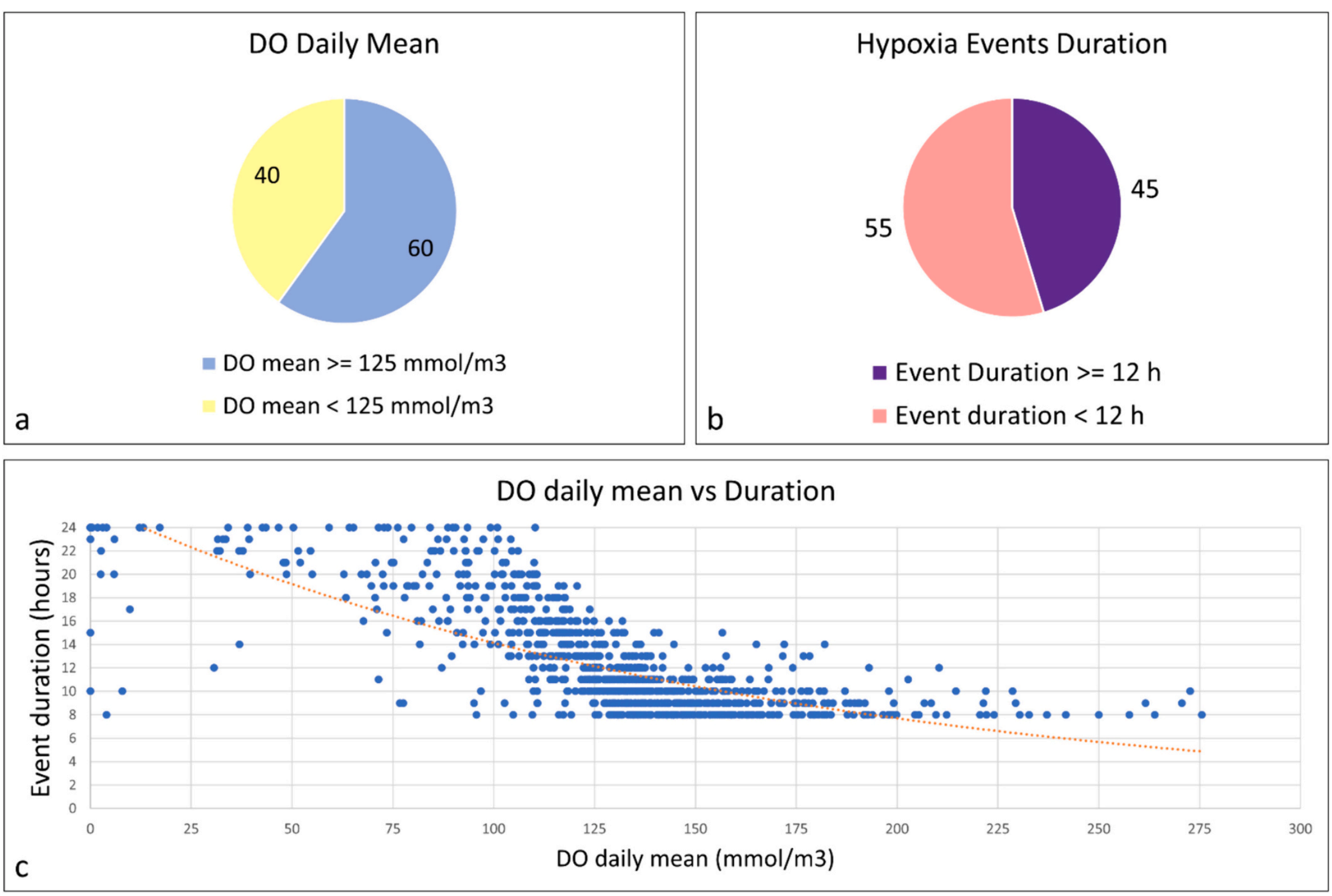

Fig. 3. General statistics of historical monitored (2008–2019) hypoxia events across the ten Venice Lagoon stations. a) Percentage of DO daily mean below or above the 125 mmol/m^3. b) Percentage of hypoxia events with a duration of less than or >12 h. c) Relation between the DO daily mean and the duration of the hypoxia event expressed in hours.

score for class 0 (i.e. *hypoxia event* occurrence), while MLP exhibit a lower F1 score for this class, as indicated by its very high precision (0.94) but lower recall (0.61), suggesting that it may miss various positive cases.

When comparing the AUC-ROC scores, Weighted SVM and XG Boost score the highest. Nevertheless, their precision and accuracy scores in class 0 are weak (e.g., 0.34 and 0.67 for precision, respectively), indicating that these algorithms are not suitable for describing this particular problem of an unbalanced dataset.

Based on these results, RF, AdaBoost and the Stacking ensemble are identified as the models with the strongest predictive power. Therefore, they have been selected as the most suitable for predicting climate change scenarios by composing the *multiple selected ML models*. Fig. 4 shows the confusion matrices for these three selected models. From these plots, it can be seen that the hypoxia class (i.e. true positive) is correctly predicted by the three models with a very similar number of times: 206 times with AdaBoost and 204 times with RF and Staking ensemble. The main difference between the three models is in the number of false positives, i.e. cases predicted in class 0 instead of class 1. The best model in this case is the Staking ensemble with 20 errors, followed by FR with 27 and AdaBoost with 31.

Moreover, sensitivity analysis shows how variations in the input data affect the predictions of the model. This type of analysis is useful for identifying the most influential features and providing a greater explainability of the results evaluating the robustness and precision of the models and analyzing the contributions of the considered variables to the outcomes. Results concerning the sensitivity analysis are reported in Fig. 5 (a, b, c). It can be seen from the figures that the three models behave differently in terms of feature importance. All the models assign significant importance to the daily mean DO concentrations. However, the RF model distributes relative importance more evenly across all the other variables. Specifically, it assigns considerable importance to water temperature and solar radiation, as well as to monthly information, humidity, and salinity (in this order). The Adaboost model places the most weight on DO, with some importance given to water temperature, while all other variables have negligible relevance. Similarly, the Stacking ensemble also prioritizes DO, but ranks solar radiation second in importance.

4.3. Future hypoxia events analysis

The hypoxia events under the RCP 8.5 business-as-usual climate change scenario are determined by averaging the simulated events generated by each selected ML model (Section 4.2) using projections of WQ and climate variables from deterministic models as input data. Results show a notable upward trend in the annual frequency of hypoxia events over time (Fig. 6.a), with the days affected by oxygen depletion increasing from 3.5 % of the reference period (20° percentile of the 2008–2019 timeframe) to 4.1 % in the mid-future and 8.8 % in the far future, which corresponds to a relative increase with respect to the reference period of +1.7 % and +4.3 % for the mid- and far-future and respectively. However, a notable increase in inter-model variability also occurs, causing a rise in uncertainty to 29 days in the mid-future and 67 days in the far future.

The seasonal analysis (Fig. 6.b) confirms the prevalence of *hypoxia events* during summer, in line with the natural processes associated with such events. However, a smaller proportion of events also occur during the autumn season. For both seasons, an increasing trend of events is predicted for 2050 and 2100 compared to the reference period. In summer, the model predicts 136 hypoxia events in 2050 and 265 in 2100, compared to 118 events observed in the reference period (indicating an average increase of 15.3 % between the reference scenario and the mid-future, followed by a further increase of 94.9 % from mid to the far-future). In autumn, 15 events are projected in 2050 and 27 in 2100, an increase of more than two and four times compared to the 6 events in the reference period. Notably, no events are predicted for winter, even in the far future. However, the model predicts a small number of events (4) during spring in 2100, indicating a possible seasonal anticipation of hypoxic events in a season where they did not occur in the reference period nor in the mid-term future.

Focusing on summertime only, Fig. 6.c shows that in the reference period, the months with the highest estimated number of *hypoxia events* are July and August, with 50 events in each month. In future simulations, there is a notable increase in occurrences, particularly in July (71 events in the mid future and 110 in the far future), while August experiences a more moderate increase, remaining nearly unchanged in the mid future (53 events) and rising to 94 events in the far future. Conversely, estimates for June show a different trend, with a decrease in *events* occurrence during the mid-future (from 15 in the reference period to 11) and a significant rise in the far future (61 events). Accordingly, the *hypoxia event* period in the far future is expected to extend, and to become more challenging for aquatic life, transitioning from the historical two-month period of July and August to a three-month duration encompassing June, July, and August.

The maps in Fig. 7 depict a comparison of hypoxia event percentages across the ten Venice Lagoon stations during the three analyzed periods: the reference, 2050, and 2100. Notably, stations 1, 5, and 7, located landward, i.e. the area with the longest water residence time (Cucco and Umgiesser, 2006), consistently exhibit the highest number of *hypoxia events* in all the three scenarios (Fig. 7.a, b, c) and the largest increase in the number of *hypoxia events* over the far future. Specifically, as illustrated in Fig. 7.d, the number of events rises from 29 in the reference period to 55 in the far future at station 1, 50 to 78 at station 5, and from 32 to 69 at station 7. Looking at stations 8, 9, and 10, where *hypoxic events* are rare or nonexistent during the reference period, there is a noticeable increasing in events, with a discernible upward trend

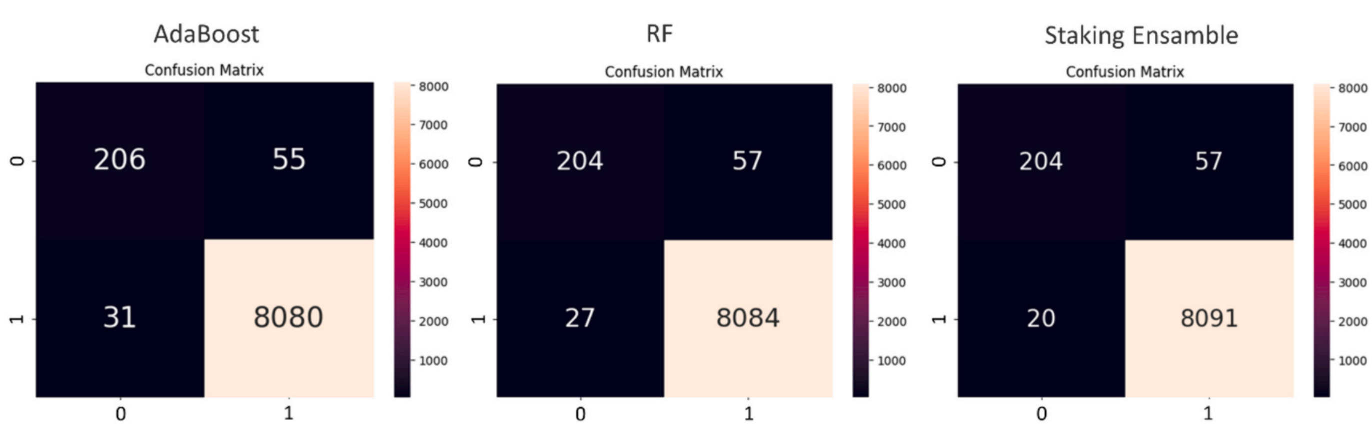

Fig. 4. Confusion matrix of the selected ML models (Adaboost, RF and Staking ensemble).

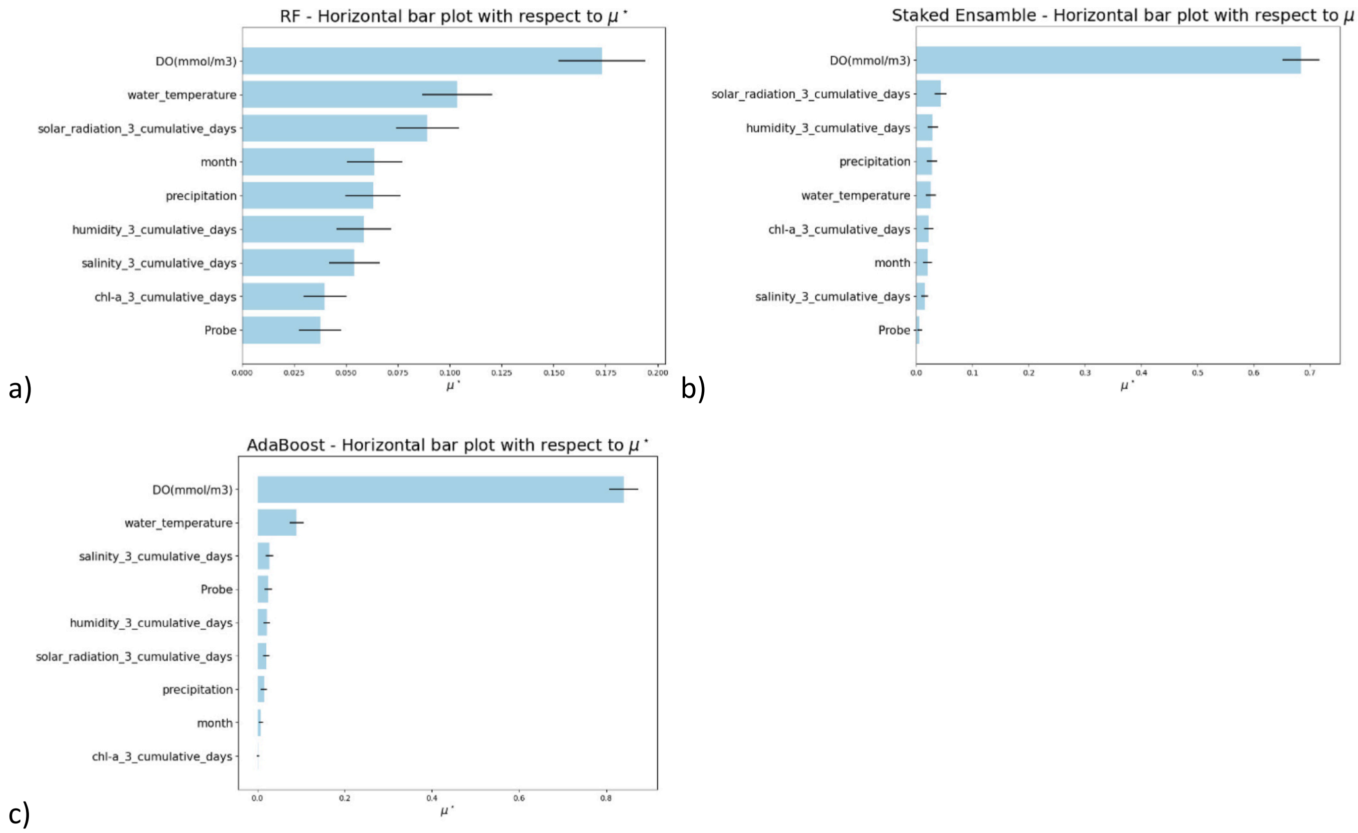

Fig. 5. Sensitivity analysis results using the Morris method for the RF (a), Staked ensemble (b), and AdaBoost (c) models.

extending from the mid to the far future. The slow circulation of water at the landward stations coupled with the changes in biogeochemical and meteorological conditions (e.g. in the present study, maximum water temperatures increase from a historical value of 32 °C to 39 °C by 2100, see Tables 1 and 2), mean that these areas of the Venice Lagoon are expected to be at risk of frequent extreme hypoxias. Stations 2 and 4 similarly display an increasing trend, although the overall number of *events* at these stations remains relatively low (maximum of 14 events) even by 2100. Lastly, stations 3 and 6, situated seaward, closest to the Malamocco inlet and channel (the largest channel of the Lagoon with a depth of 14 m (Ghezzo et al., 2010)), remain in a well-oxygenated state, with no *hypoxic events* expected for the mid and far future.

The uncertainty bars in Fig. 7.d, depicting variability in predictions among the selected ML models, emphasize stations 1, 9, and 10 as particularly susceptible to high variability. These bars illustrate a wide min-max range of potential *hypoxia events*. For instance, at station 1, events in 2100 could vary from as high as 90 to as low as 36. Despite these ML model-related fluctuations, all the results suggest that the Venice Lagoon will be more prone to *hypoxic events* in the mid and especially in the far future, under climatic conditions induced by the business-as-usual scenario.

5. Discussion

Hypoxic conditions can frequently occur in lagoon areas subject to reduced water exchange, in the warmer season, and mainly at night, especially in the layers close to the sediment (Diaz and Rosenberg, 2008). Future trends of DO in marine waters are a key topic of climate research due to the essential role of DO in sustaining marine life. However, DO dynamics are difficult to assess with deterministic models due to the complex interactions among a number of physical and biological drivers (Cossarini et al., 2021; Di Biagio et al., 2022; Mussap et al., 2016). Indeed, oxygen dynamics involve a range of interconnected processes, including mixing, water residence time, and daily oxygen fluctuations, which collectively influence the spatial and temporal distribution of oxygen depletion. In stratified systems like the Venice Lagoon, mixing driven by tides, wind, and temperature gradients plays a key role in oxygen distribution, with insufficient mixing often leading to oxygen depletion in bottom waters (Geyer et al., 2018). Additionally, the residence time of water masses determines the duration over which biological and chemical processes, such as respiration and organic matter decay, can consume available oxygen (Kjerfve and Magill, 2019). Daily variations, driven by photosynthesis during the day and respiration at night, introduce diurnal shifts in oxygen levels, often resulting in nighttime hypoxia in the shallow areas (Cloern, 2001). The SHYFEM-BFM model applied in this methodology addresses these dynamics in detail, and this is essential for a comprehensive analysis of oxygen depletion in the Venice Lagoon. Indeed, the simulation of the key biogeochemical processes in marine ecosystem, tracking the cycles of nutrients, carbon, oxygen, a pool of phytoplankton, zooplankton and bacteria across the modeled system, coupled with the hydro-morphological dynamics accounting for time variable inputs, boundary conditions and meteorological forcing such as river inputs of water and nutrients, exchange of water and biogeochemical variables with the sea, and meteorological forcing.

The projected large increase in *hypoxia events* occurrence in the far future (Figs. 5 and 6) points to worrying impacts on shallow estuaries and coastal ecosystems such as the Venice Lagoon in the absence of mitigation of carbon emissions. Exacerbating environmental degradation, such as the transition of the duration of hypoxia events in the Venice Lagoon from two to three months, could indeed pose a major challenge to aquatic life. The results highlight highest vulnerability to hypoxic conditions of landward sites compared to open waters due to the combination of slow water renewal times and a strong climate sensitivity of shallow waters to the increase in air temperature. Among all the environmental changes considered in climate projections, the

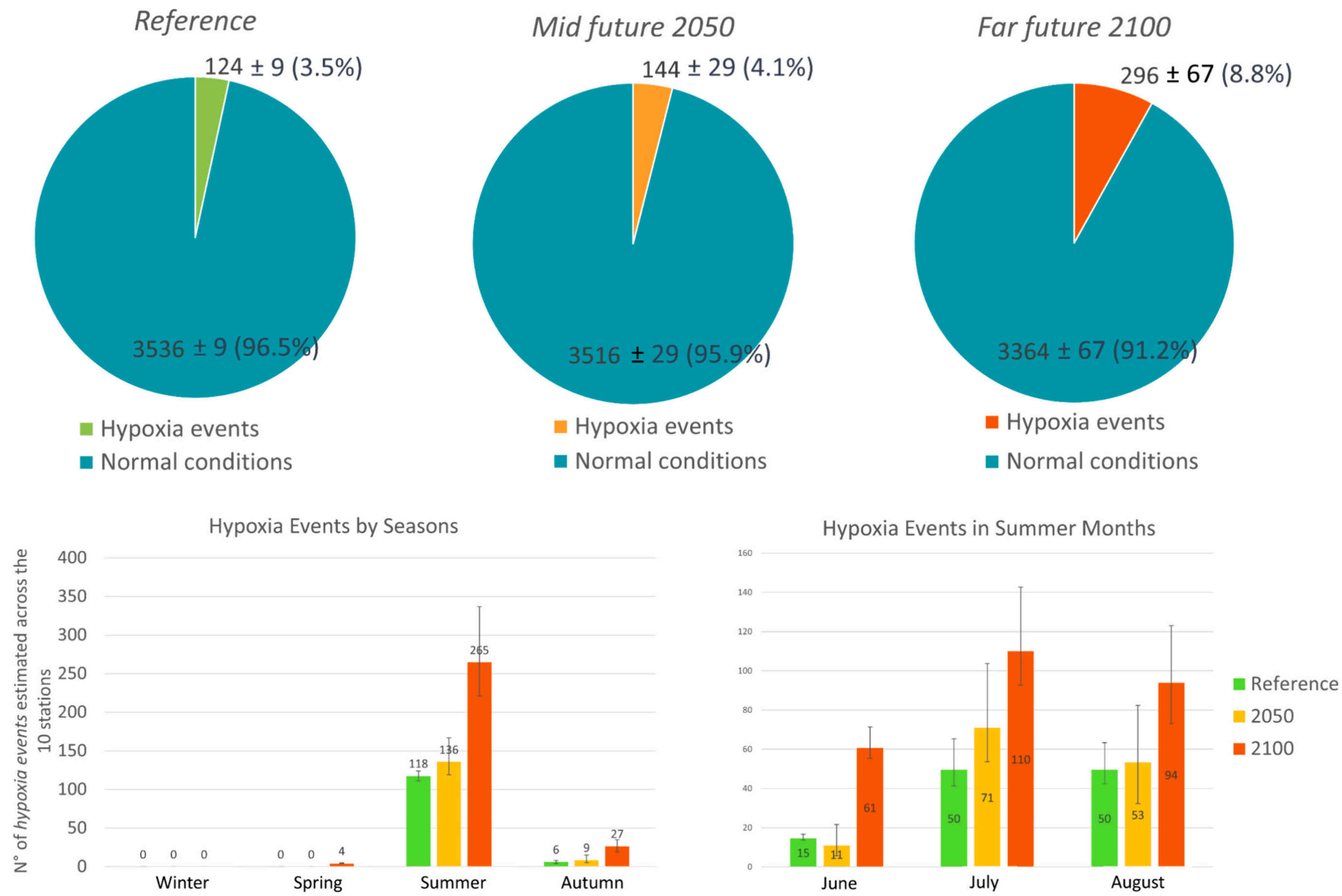

Fig. 6. Temporal dimension of hypoxia scenarios designed by the ML-BGC&Climate model, across the reference period and the mid and far future in the ten Venice Lagoon stations. a) Pie charts indicating the count and the relative percentage of hypoxia events over the entire period. B) Bar plots indicating the number of hypoxia events estimated in each season. c) Bar plots indicating the number of hypoxia events estimated in each summer month. The error bars represent the predictions variability given by the whole range of the selected models.

temperature is undoubtedly a key factor driving these changes. Indeed, increasing temperatures contribute to a reduction in the solubility of oxygen in seawater (Garcia Herncin and Gordon Louis, 1992) and stimulate the metabolic activity of aquatic organisms (Hsieh et al., 2021) leading to heightened oxygen biological demand (Sokolova and Lannig, 2008).

5.1. *Case study considerations*

The hybrid model envisages more frequent and longer-lasting periods subjected to oxygen depletion in the RCP 8.5 scenario (Figs. 5 and 6). These evaluations, appear to run counter to the goals outlined in the EU reference Mission, particularly the Starfish 2030 initiative titled 'Restore our Ocean and Waters Report of the Mission Board – Healthy Oceans, Seas, Coastal and Inland Waters'. In particular, these estimations depict a scenario for the Venice Lagoon that departs from one of the main goals of Starfish 2030: to attain zero pollution of our oceans and waters by 2030, which entails, among others, cutting down hypoxia by at least 50 %. Furthermore, the estimation of an increased risk of hypoxia can also be aggravated by other factors not included in this methodology: *firstly*, is likely that some areas of the Venice Lagoon could experience *hypoxia events* in a more massive way in the deeper waters immediately above the sediments. Indeed, it should be considered that shallow coastal lagoons often exhibit a significant decrease in oxygen concentration with depth (Brigolin et al., 2021; Hsieh et al., 2021), coupled with intense dynamics of the daily cycle of oxygen concentration. Moreover, higher sea surface temperatures also lead to density stratification, which can greatly reduce vertical mixing and thus restricts the transport of oxygen to deeper layers (Howarth et al., 2011). *Secondly*, it's plausible that the MOSE system could potentially heighten the risk of hypoxia by impeding the exchange of seawater with the Lagoon. With the projected sea level rise in the mid and far future, the MOSE barriers might be activated for more extended periods (for example, 4 or 5 consecutive days), leading to a disruption in seawater inflow. However, more targeted studies are necessary to examine these aspects in detail, particularly since the MOSE system has been operational since 2020 and the available data are not enough for robust analysis. These studies would help assess the precise impact of the MOSE system on water exchange patterns and the potential implications for hypoxia risk in the Venice Lagoon. *Thirdly*, it is possible that future scenarios of land use change, urbanization and population growth could also negatively affect the occurrence of *hypoxia events*. Indeed, in a business-as-usual scenario, high levels of nutrients discharged into the lagoon during both dry and wet periods can trigger microbial growth. During dry periods, phytoplankton can produce large amounts of particulate organic carbon and consume nutrients and oxygen in the water column. Oxygen depletion is more pronounced during wet periods, when heavy rainfall, which brings turbid water with high concentrations of nitrogenous nutrients, can stimulate phytoplankton growth, and increase the discharge of particulate organic carbon and dissolved organic carbon into the lagoon. Indeed, negative correlations between DO and dissolved organic carbon and DO and particulate organic carbon can be observed in both seasons, suggesting that heterotrophic bacteria may largely use dissolved oxygen in the water column (Hsieh et al., 2021).

Fig. 7. Spatial dimension of hypoxia scenarios designed by the ML-BGC&Climate model. Pie charts visualizing the a) reference, b) mid future and c) far future scenarios across the ten Venice Lagoon stations. d) Bar plots indicating the number of hypoxia events across the reference period and the mid and far future in the ten Venice Lagoon stations. The error bars represent the predictions variability given by the whole range of the selected models.

5.2. Scientific context and the relevance for society

The new findings from this research, both in terms of methodology and results, should be considered valuable examples to be applied in other case studies. Although there are already some papers in the literature that address advanced modeling of DO and hypoxia using ML in a sophisticated manner, such as Yu et al. (2020), which proposed a model with three major components: empirical orthogonal functions analysis, automatic selection of forcing transformation, and neural network training. Using this method, they indicate in some maps the different magnitudes to which the DO concentration changes over time. For example, during the summer months, the DO of the entire bay decreases from the long-term mean value, with the maximum decrease occurring in the region with deep waters. Liang et al. (2023) pioneered the integration of four-dimensional spatiotemporal characteristics in DO forecasting, crucial for early warning systems. It highlighted that human activities, such as submarine groundwater discharge, impact DO levels, especially by influencing chemical reactions.

Regarding predicting the medium and long-term future, exceptionally Pezner et al. (2023) consider such a long-term perspective. They focused on future DO levels under different climate scenarios on coral reefs. They found widespread hypoxia, with 94 % of reefs expected to experience weak to moderate hypoxia by 2100 under severe climate change. However, they only considered temperature effects, while the current study integrates multiple factors. Nevertheless, Pezner et al. estimate future changes only in water temperature and calculate the impact of warming on solubility but do not consider the effect of climate change on other relevant variables as shown in the presented study. Indeed, the scenario analysis proposed here incorporates future projections of some of the most relevant hypoxia response variables.

Among the different implications the methodology and results of the multi-component model can have within the international community it can be mentioned:

- It can provide robust scenarios that are useful for better management and adaptation to current and future climate change risks. Indeed, the scenarios, as developed by the combined approach of using ML and deterministic model projections, are based on processes that leverage both, the extrapolation generalization capabilities of advanced ML methods and the interpretability of numerical simulations, thus exploiting the strengths of both modeling approaches and overcoming the limitations of each. On one side ML predictions are reliable in the short term, indeed the development of long-lasting scenarios using ML alone still does not seem to be scientifically robust; on the other side, deterministic models tend to flatten the distribution curve in the medium and long-term by eliminating extremes.
- It can help observational scientists extend their knowledge to new estimates, paving the way for the identification of hotspots for the design and implementation of powerful restoration actions, which can accelerate the recovery of local ecosystems threatened by climate change. Given the oxygen dynamics underlying hypoxia events, several measures can be considered In response to these increases, such as nutrient loading reduction, eutrophication control, and oxygenation. Effective interventions include riparian buffer zones, seagrass transplantation, and saltmarsh restoration. These measures, in the Venice Lagoon, can influence water quality by nutrient retention, oxygen release, and restoring natural gradients, thereby reducing hypoxia risk. Comprehensive adaptation strategies must explore synergies between various restoration measures to maximise ecosystem service provisioning and cumulative risk reduction.
- It could act as a prototype for future digital tools that can benefit stakeholders, including the aquaculture and fisheries industries, seeking to manage the risk of this water-related extreme event to their products.
- The methodology offers significant novelty and potential applicability to other coastal systems, making it valuable to the international

community. It may encourage both scientists and coastal managers to replicate the approach in their case studies. The methodology is particularly useful for assessing whether hypoxia, even if not highly prevalent today and/or in the past, could become a serious threat in the future under certain climatic conditions. However, there is considerable potential to refine and improve the methodology to overcome its limitations. In particular, one key challenge lies in addressing model uncertainties, as it is difficult to quantify the cumulative uncertainty across the multiple models used. From a data perspective, additional historical data (e.g., a longer timeframe) could help reduce uncertainties in ML models. Similarly, for future scenarios, having continuous data over extended periods, rather than just one-year timeframes, would likely enhance the accuracy of the projections. Lastly, a more comprehensive study should consider all climate scenarios, i.e. 1.9, 2.6, 3.4, 4.5, 6, 7, and 8.5 to provide stakeholders with a complete range of possibilities rather than focusing solely on the most severe emission scenario. Finally, the intercomparisons between CMIP5 and CMIP6 biogeochemical projections done with global models could be used to discuss the results in respect to the new CMIP6 projections.

6. Conclusions

To add insights into past (2008–2019) and future (2050, 2100) hypoxia events in shallow coastal environments such as the Venice Lagoon a multivariate analysis using a combination of seven ML models and two deterministic models (hydrodynamic-biogeochemical SHYFEM-BFM and climate COSMO-CLM) is applied, addressing the major challenge of dealing with an unbalanced dataset which characterise extreme events. Touching on several aspects, the main conclusions are summarized as follows:

- ML for unbalanced dataset: Adaboost, RF and the Staking ensemble ML models achieve good classification performances, reaching 8.4 and 1 of the F1 score for the *hypoxia class* and the *normal class* respectively. The estimates point out that testing multiple ML models is necessary to overcome the limitations of some algorithms in dealing with unbalanced data sets. Moreover, combining the results ensembling multiple models enables the assessment of algorithm-related uncertainty in the scenario analysis.
- Hypoxias in the future: The hypoxia events scenario analysis in the Venice Lagoon case study under RCP8.5 reveals interesting findings: according to the model estimates, the Lagoon (and especially the landward areas) is expected to become more prone to an increase in hypoxic events in the mid (with an increase of 0.6 % respect to the reference period) and especially in the far future (with an increase of 5.3 % respect to the reference period) as a result of business-as-usual climate conditions. The summer season appears to be extended, shifting from the historical two-month period of July and August to a three-month duration of June, July, and August.
- Climate change adaptation and mitigation: These results should be seen as a wake-up call, highlighting the fact that business-as-usual emissions management could lead to harmful changes in the WQ of the Venice Lagoon, with cascading effects on the life and health of the entire ecosystem. The data- and numerical-based findings highlight the urgency of becoming aware of and addressing the management of the Venice Lagoon, as well as other vulnerable water bodies, to prevent adverse hypoxia events. A proactive approach aims to ensure the maintenance of WQ and aligns with the objectives outlined in initiatives such as EU Mission 2030's goals, including 'digitalization in environmental assessment' and 'Healthy Oceans, Seas, Coastal and Inland Waters'.
- The governance aspect: Encouraging policymakers and stakeholders to take necessary scientific-based actions is crucial for the effective management and preservation of these aquatic environments. Implementing measures, such as establishment of riparian buffer zones, seagrass transplantation, saltmarsh restoration and/or creation, and the re-establishment of lagoon's hydrology to prevent and mitigate hypoxia events, will contribute significantly to safeguarding the health and sustainability of these vital water systems.

CRediT authorship contribution statement

Federica Zennaro: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Elisa Furlan:** Writing – review & editing, Investigation, Funding acquisition, Conceptualization. **Donata Canu:** Validation, Methodology, Investigation. **Leslie Aveytua Alcazar:** Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation. **Ginevra Rosati:** Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation. **Cosimo Solidoro:** Supervision, Investigation. **Andrea Critto:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the Ph.D. programme in Science and Management of Climate Change of Ca' Foscari University of Venice (Ph. D. research grant), and by the REST-COAST project funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101037097. Moreover, scientific activities were performed with the contribution of the Provveditorato for the Public Works of Veneto, Trentino Alto Adige, and Friuli Venezia Giulia, provided through the concessionary of State Consorzio Venezia Nuova and coordinated by CORILA.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.marpolbul.2024.117028.

References

Ahmed, U., Mumtaz, R., Anwar, H., Shah, A.A., Irfan, R., García-Nieto, J., 2019. Efficient water quality prediction using supervised machine learning. Water 11 (11), 2210.

Anelli Monti, M., Brigolin, D., Franzoi, P., Libralato, S., Pastres, R., Solidoro, C., Zucchetta, M., Pranovi, F., 2021. Ecosystem functioning and ecological status in the Venice lagoon, which relationships? Ecol. Indic. 133, 108461. https://doi.org/10.1016/j.ecolind.2021.108461.

Baldi, P., Brunak, S., Chauvin, Y., Andersen, C.A.F., Nielsen, H., 2000. Assessing the accuracy of prediction algorithms for classification: an overview. Bioinformatics 16 (5), 412–424. https://doi.org/10.1093/bioinformatics/16.5.412.

Baxter, J.M., 2019. Ocean deoxygenation: everyone's problem. Causes, impacts, consequences and solutions. In: Ocean Deoxygenation: Everyone's Problem. Causes, Impacts, Consequences and Solutions. https://doi.org/10.2305/iucn.ch.2019.13.en.

Beck, N.G., Bruland, K.W., 2000. Diel biogeochemical cycling in a hyperventilating shallow estuarine environment. Estuaries 23, 177–187.

Bendoricchio, G., De Boni, G., 2005. A water-quality model for the Lagoon of Venice, Italy. Ecological Modelling 184 (1), 69–81. https://doi.org/10.1016/j.ecolmodel.2004.11.013.

Berti, M., Scardia, F., Carrer, C., Sorrentino, F., 2022. Analysis of a comprehensive monthly dataset on nitrogen, phosphorus and organic carbon in the Venice lagoon waters (Italy). EQA-International Journal of Environmental Quality 49, 1–11 (doi:110.6092/issn.2281-4485/14871).

Bisong, E., 2019. Logistic regression. In: Building Machine Learning and Deep Learning Models on Google Cloud Platform: A Comprehensive Guide for Beginners, pp. 243–250.

Bon, M., Mainardi, D., Mizzan, L., Torricelli, P., 2001. The biodiversity in the Venice lagoon as the basis of a sustainability project. In: Sustainable Venice: Suggestions for the Future. Springer Netherlands, Dordrecht, pp. 27–60.

Breitburg, D., Levin, L.A., Oschlies, A., Grégoire, M., Chavez, F.P., Conley, D.J., Garçon, V., Gilbert, D., Gutiérrez, D., Isensee, K., Jacinto, G.S., Limburg, K.E., Montes, I., Naqvi, S.W.A., Pitcher, G.C., Rabalais, N.N., Roman, M.R., Rose, K.A., Seibel, B.A., Zhang, J., 2018. Declining oxygen in the global ocean and coastal waters. Science 359 (6371). https://doi.org/10.1126/science.aam7240.

Brigolin, D., Rabouille, C., Demasy, C., Bombled, B., Monvoisin, G., Pastres, R., 2021. Early diagenesis in sediments of the Venice Lagoon (Italy) and its relationship to hypoxia. Front. Mar. Sci. 7 (January), 1–15. https://doi.org/10.3389/fmars.2020.575547.

Bucchignani, E., Montesarchio, M., Zollo, A.L., Mercogliano, P., 2016. High-resolution climate simulations with COSMO-CLM over Italy: performance evaluation and climate projections for the 21st century. Int. J. Climatol. 36 (2).

Canu, D.M., Aveytua-Alcazar, L., Laurent, C., Rosati, G., Solidoro, C., 2023. Is the Future Given? Cumulative Impact of Climate Change and MOSE Closures on Venice and Its Lagoon.

Çevirgen, S., Elwany, H., Pesce, M., A, Z., 2020. Managing nutrient pollution in Venice Lagoon (Italy): a practical tool for assessment of water quality. Sustainable Water Resources Management 6 (3), 1–13. https://doi.org/10.1007/s40899-020-00390-y.

Cheek, A.O., Landry, C.A., Steele, S.L., Manning, S., 2009. Diel hypoxia in marsh creeks impairs the reproductive capacity of estuarine fish populations. Mar. Ecol. Prog. Ser. 392, 211–221.

Chen, T., Guestrin, C., 2016. Xgboost: A scalable tree boosting system. In: Proceedings of the 22nd acm sigkdd International Conference on Knowledge Discovery and Data Mining, pp. 785–794. August.

Cladas, Y., Papantoniou, G., Bekiari, V., Fragkopoulu, N., 2016. Dystrophic crisis event in Papas lagoon, Araxos Cape, western Greece in the summer 2012. Mediterr. Mar. Sci. 17 (1), 32–38.

Cloern, J.E., 2001. Our evolving conceptual model of the coastal eutrophication problem. Mar. Ecol. Prog. Ser. 210, 223–253.

Cornell, L.P., Klarer, D.M., 2008. Patterns of dissolved oxygen, productivity and respiration in Old Woman Creek Estuary, Erie County, Ohio during low and high water conditions. Ohio J. Sci. 108 (3), 31.

Cossarini, G., Feudale, L., Teruzzi, A., Bolzon, G., Coidessa, G., Solidoro, C., Salon, S., 2021. High-resolution reanalysis of the Mediterranean Sea biogeochemistry (1999–2019). Front. Mar. Sci. 8, 741486.

Cucco, A., Umgiesser, G., 2006. Modeling the Venice Lagoon residence time. Ecol. Model. 193 (1), 34–51. https://doi.org/10.1016/j.ecolmodel.2005.07.043.

CVN, 1997. Allegato allo studio di impatto ambientale del progetto di massima delle opere mobili per la difesa dei centri abitati lagunari dagli allagamenti, p. 2.

Di Biagio, V., Salon, S., Feudale, L., Cossarini, G., 2022. Subsurface oxygen maximum in oligotrophic marine ecosystems: mapping the interaction between physical and biogeochemical processes. Biogeosci. Discuss. 2022, 1–33.

Diamond, J.S., Moatar, F., Recoura-Massaquant, R., Chaumot, A., Zarnetske, J., Valette, L., Pinay, G., 2023. Hypoxia is common in temperate headwaters and driven by hydrological extremes. Ecol. Indic. 147, 109987.

Diaz, R.J., Rosenberg, R., 1995. Marine benthic hypoxia: a review of its ecological effects and the behavioural responses of benthic macrofauna. Oceanogr. Mar. Biol. Annu. Rev. 33 (245), 03.

Diaz, R.J., Rosenberg, R., 2008. Spreading dead zones and consequences for marine ecosystems. Science 321 (5891), 926–929.

Du, J., Shen, J., Park, K., Wang, Y.P., Yu, X., 2018. Worsened physical condition due to climate change contributes to the increasing hypoxia in Chesapeake Bay. Sci. Total Environ. 630, 707–717. https://doi.org/10.1016/j.scitotenv.2018.02.265.

Duvall, M.S., Jarvis, B.M., Wan, Y., 2022. Impacts of climate change on estuarine stratification and implications for hypoxia within a shallow subtropical system. Estuar. Coast. Shelf Sci. 279. https://doi.org/10.1016/j.ecss.2022.108146.

Facca, C., Ceoldo, S., Pellegrino, N., Sfriso, A., 2014. Natural recovery and planned intervention in coastal wetlands: Venice Lagoon (Northern Adriatic Sea, Italy) as a case study. Scientific World Journal 2014, 968618. https://doi.org/10.1155/2014/968618.

Fisher, M.C., Moore, S.K., Jardine, S.L., Watson, J.R., Samhouri, J.F., 2021. Climate shock effects and mediation in fisheries. Proc. Natl. Acad. Sci. 118 (2), e2014379117.

Freund, Yoav, Schapire, Robert E., 1997. A decision-theoretic generalization of on-line learning and an application to boosting. J. Comput. Syst. Sci. 55 (1), 119–139. ISSN 0022-0000. https://doi.org/10.1006/jcss.1997.1504.

Garcia Herncin, E., Gordon Louis, I., 1992. Oxygen solubility in seawater: better fitting equations. Limnol. Oceanogr. 37. https://doi.org/10.4319/lo.1992.37.6.1307.

Geyer, W.R., MacCready, P., Burchard, H., 2018. Turbulence in estuaries. Ann. Rev. Mar. Sci. 10, 235–258.

Ghezzo, M., Guerzoni, S., Cucco, A., Umgiesser, G., 2010. Changes in Venice Lagoon dynamics due to construction of mobile barriers. Coast. Eng. 57 (7), 694–708. https://doi.org/10.1016/j.coastaleng.2010.02.009.

Gruber, N., Boyd, P.W., Frölicher, T.L., Vogt, M., 2021. Biogeochemical extremes and compound events in the ocean. Nature 600 (7889), 395–407. Nature Research. https://doi.org/10.1038/s41586-021-03981-7.

Haghighi, S., Jasemi, M., Hessabi, S., Zolanvari, A., 2018. PyCM: multiclass confusion matrix library in Python. Journal of Open Source Software 3 (25), 729. https://doi.org/10.21105/joss.00729.

Howarth, R., Chan, F., Conley, D.J., Garnier, J., Doney, S.C., Marino, R., Billen, G., 2011. Coupled biogeochemical cycles: eutrophication and hypoxia in temperate estuaries and coastal marine ecosystems. Front. Ecol. Environ. 9 (1), 18–26.

Hsieh, H.H., Chuang, M.H., Shih, Y.Y., Weerakkody, W.S., Huang, W.J., Hung, C.C., Muller, F.L.L., Ranatunga, R.R.M.K.P., Wijethunga, D.S., 2021. Eutrophication and hypoxia in tropical Negombo Lagoon, Sri Lanka. Frontiers in Marine Science 8. https://doi.org/10.3389/fmars.2021.678832.

Intergovernmental Panel on Climate Change, 2014. Climate change 2014: synthesis report. In: Contribution of Working Groups 646 I. II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, p. 151.

Justić, D., Rabalais, N.N., Turner, R.E., 1996. Effects of climate change on hypoxia in coastal waters: a doubled CO2 scenario for the northern Gulf of Mexico. Limnol. Oceanogr. 41 (5), 992–1003. https://doi.org/10.4319/lo.1996.41.5.0992.

Khani, S., Rajaee, T., 2017. Modeling of dissolved oxygen concentration and its hysteresis behavior in rivers using wavelet transform-based hybrid models. CLEAN–Soil, Air, Water 45 (2).

Kjerfve, B., Magill, K.E., 2019. Hydrodynamics of estuaries. In: Middleton, W.E.K. (Ed.), Estuarine and Coastal Modeling. American Society of Civil Engineers, pp. 5–25.

Kwiatkowski, L., Torres, O., Bopp, L., Aumont, O., Chamberlain, M., Christian, J.R., Ziehn, T., 2020. Twenty-first century ocean warming, acidification, deoxygenation, and upper-ocean nutrient and primary production decline from CMIP6 model projections. Biogeosciences 17 (13), 3439–3470.

Lamy, P., Citores, A., Deidun, A., Evans, L., Galgani, F., Heffernan, P., Pons, G., 2020. Mission Starfish 2030: restore our ocean and waters. In: Report of the Mission Board Healthy Oceans. Seas, Coastal and Inland Waters.

Lee, H.H., Chang, C.C., Shieh, M.J., Wang, J.P., Chen, Y.T., Young, T.H., Hung, S.C., 2013. Hypoxia enhances chondrogenesis and prevents terminal differentiation through PI3K/Akt/FoxO dependent anti-apoptotic effect. Sci. Rep. 3 (1), 2683.

Lehrter, J., Ko, D., Lowe, L., Penta, B., 2017. Predicted effects of climate change on northern Gulf of Mexico hypoxia. In: Modeling Coastal Hypoxia: Numerical Simulations of Patterns, Controls and Effects of Dissolved Oxygen Dynamics, pp. 173–214. https://doi.org/10.1007/978-3-319-54571-4_8.

Leoni, S., Dominik, J., Cassin, D., Manfè, G., Tagliapietra, D., Acri, F., Zonta, R., 2022. Sediment oxygen demand rate in a flow regulated lagoon (Venice, Italy). Front. Environ. Sci. 10, 1000665.

Liang, W., Liu, T., Wang, Y., Jiao, J.J., Gan, J., He, D., 2023. Spatiotemporal-aware machine learning approaches for dissolved oxygen prediction in coastal waters. Sci. Total Environ. 905, 167138.

Liaw, A., Wiener, M., 2002. Classification and regression by randomForest. R news 2 (3), 18–22.

Lionello, P., Nicholls, R.J., Umgiesser, G., Zanchettin, D., 2021. Venice flooding and sea level: past evolution, present issues, and future projections (introduction to the special issue). Nat. Hazards Earth Syst. Sci. 21 (8), 2633–2641.

Lovato, T., Vichi, M., Oddo, P., 2013. High-resolution simulations of Mediterranean Sea physical oceanography under current and scenario climate conditions: model description, assessment and scenario analysis. CMCC Res. Pap. 207.

Luke, A., Sefton-Green, J., Graham, P., Kellner, D., Ladwig, J., 2017. Digital ethics, political economy, and the curriculum: this changes everything. In: Handbook of Writing, Literacies, and Education in Digital Cultures. Routledge, pp. 251–262.

Meier, Markus, Dieterich, C., Gröger, M., 2021. Natural variability is a large source of uncertainty in future projections of hypoxia in the Baltic Sea. Commun. Earth Environ. 2 (1), 50.

Melaku Canu, D., Umgiesser, G., Solidoro, C., 2001. Short-term simulations under winter conditions in the lagoon of Venice: a contribution to the environmental impact assessment of temporary closure of the inlets. Ecological Modelling 138. http://www.salve.it/uk/attivita/OPERE/.

Micheletti, C., Gottardo, S., Critto, A., Chiarato, S., Marcomini, A., 2011. Environmental quality of transitional waters: the lagoon of Venice case study. Environ. Int. 37 (1), 31–41. https://doi.org/10.1016/j.envint.2010.06.009.

Morris, M.D., 1991. Factorial sampling plans for preliminary computational experiments. Technometrics 33 (2), 161–174.

Munari, C., Mistri, M., 2011. Short-term hypoxia modulates Rapana venosa (Muricidae) prey preference in Adriatic lagoons. J. Exp. Mar. Biol. Ecol. 407 (2), 166–170. https://doi.org/10.1016/j.jembe.2011.06.003.

Mussap, G., Zavatarelli, M., Pinardi, N., Celio, M., 2016. A management oriented 1-D ecosystem model: implementation in the Gulf of Trieste (Adriatic Sea). Reg. Stud. Mar. Sci. 6, 109–123.

Oschlies, A., Brandt, P., Stramma, L., Schmidtko, S., 2018. Drivers and mechanisms of ocean deoxygenation. Nat. Geosci. 11 (7), 467–473.

Paerl, H.W., 2006. Assessing and managing nutrient-enhanced eutrophication in estuarine and coastal waters: interactive effects of human and climatic perturbations. Ecol. Eng. 26 (1), 40–54. https://doi.org/10.1016/j.ecoleng.2005.09.006.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Duchesnay, É., 2011. Scikit-learn: machine learning in Python. The Journal of machine Learning research 12, 2825–2830.

Pena, M.A., Katsev, S., Oguz, T., Gilbert, D., 2010. Modeling dissolved oxygen dynamics and hypoxia. Biogeosciences 7 (3), 933–957.

Pérez-Ruzafa, A., Pérez-Ruzafa, I.M., Newton, A., Marcos, C., 2019. Coastal lagoons: environmental variability, ecosystem complexity, and goods and services uniformity. In: Coasts and Estuaries. Elsevier, pp. 253–276.

Pesce, M., Critto, A., Torresan, S., Giubilato, E., Santini, M., Zirino, A., Ouyang, W., Marcomini, A., 2018. Modelling climate change impacts on nutrients and primary production in coastal waters. Sci. Total Environ. 628–629, 919–937. https://doi.org/10.1016/j.scitotenv.2018.02.131.

Pezner, A.K., Courtney, T.A., Barkley, H.C., et al., 2023. Increasing hypoxia on global coral reefs under ocean warming. Nat. Clim. Chang. 13, 403–409. https://doi.org/10.1038/s41558-023-01619-2.

Politikos, D.V., Petasis, G., Katselis, G., 2021. Interpretable machine learning to forecast hypoxia in a lagoon. Eco. Inform. 66 (July), 101480. https://doi.org/10.1016/j.ecoinf.2021.101480.

Qi, D., Majda, A.J., 2022. Using Machine Learning to Predict Extreme Events in Complex Systems. https://doi.org/10.1073/pnas.1917285117/-/DCSupplemental.y.

Reale, M., Cossarini, G., Lazzari, P., Lovato, T., Bolzon, G., Masina, S., Salon, S., 2022. Acidification, deoxygenation, and nutrient and biomass declines in a warming Mediterranean Sea. Biogeosciences 19 (17), 4035–4065.

Renaud, M.L., 1986. Detecting and avoiding oxygen deficient sea water by brown shrimp, Penaeus aztecus (Ives), and white shrimp Penaeus setiferus (Linnaeus). J. Exp. Mar. Biol. Ecol. 98 (3), 283–292.

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Rafaj, P., 2011. RCP 8.5—a scenario of comparatively high greenhouse gas emissions. Clim. Chang. 109, 33–57.

Rockel, B., Geyer, B., 2008. The performance of the regional climate model CLM in different climate regions, based on the example of precipitation. Meteorol. Z. (Berlin) 17.

Sampaio, E., Santos, C., Rosa, I.C., Ferreira, V., Pörtner, H.-O., Duarte, C.M., Levin, L.A., Rosa, R., 2021. Impacts of hypoxic events surpass those of future ocean warming and acidification. Nature Ecology & Evolution 5 (3), 311–321. https://doi.org/10.1038/s41559-020-01370-3.

Serinaldi, F., Kilsby, C.G., 2015. Stationarity is undead: uncertainty dominates the distribution of extremes. Adv. Water Resour. 77, 17–36.

Serinaldi, F., Kilsby, C.G., Lombardo, F., 2018. Untenable nonstationarity: an assessment of the fitness for purpose of. trend tests in hydrology. Adv. Water Resour. 111, 132–155.

Sfriso, A., Facca, C., 2007. Distribution and production of macrophytes and phytoplankton in the lagoon of Venice: comparison of actual and past situation. In: Lagoons and Coastal Wetlands in the Global Change Context: Impacts and Management Issues: Selected Papers of the International Conference "CoastWetChange", Venice, 26–28 April 2004. Springer Netherlands, pp. 71–85.

Sfriso, A., Curiel, D., Rismondo, A., 2009. The Lagoon of Venice.

Sokolova, I.M., Lannig, G., 2008. Interactive effects of metal pollution and temperature on metabolism in aquatic ectotherms: implications of global climate change. Clim. Res. 37 (2–3), 181–201.

Solidoro, C., Pastres, R., Cossarini, G., Ciavatta, S., 2004. Seasonal and spatial variability of water quality parameters in the lagoon of Venice. J. Mar. Syst. 51 (1–4 SPEC. ISS), 7–18. https://doi.org/10.1016/j.jmarsys.2004.05.024.

Solidoro, C., Bandelj, V., Bernardi, F.A., Camatti, E., Ciavatta, S., Cossarini, G., Facca, C., Franzoi, P., Libralato, S., Canu, D.M., Pastres, R., Pranovi, F., Raicevich, S., Socal, G., Sfriso, A., Sigovini, M., Tagliapietra, D., Torricelli, P., 2010. Response of the Venice Lagoon Ecosystem to Natural and Anthropogenic Pressures over the Last 50 Years.

Sonnewald, M., Lguensat, R., Jones, D.C., Dueben, P.D., Brajard, J., Balaji, V., 2021. Bridging observations, theory and numerical simulation of the ocean using machine learning. Environ. Res. Lett. 16 (7), 073008.

Steppeler, J., Bitzer, H.W., Schättler, U., 2003. New developments concerning the Z-coordinate version of the LM. COSMO Newsl. 3, 177–178.

Tellier, J.M., Kalejs, N.I., Leonhardt, B.S., Cannon, D., Höök, T.O., Collingsworth, P.D., 2022. Widespread prevalence of hypoxia and the classification of hypoxic conditions in the Laurentian Great Lakes. Journal of Great Lakes Research 48 (1), 13–23. International Association of Great Lakes Research. https://doi.org/10.1016/j.jglr.2021.11.004.

Tramblay, Y., Koutroulis, A., Samaniego, L., Vicente-Serrano, S.M., Volaire, F., Boone, A., Le Page, M., Llasat, M.C., Albergel, C., Burak, S., Cailleret, M., Kalin, K.C., Davi, H., Dupuy, J.L., Greve, P., Grillakis, M., Hanich, L., Jarlan, L., Martin-StPaul, N., Polcher, J., 2020. Challenges for drought assessment in the Mediterranean region under future climate scenarios. In: Earth-Science Reviews, vol. 210. Elsevier B.V. https://doi.org/10.1016/j.earscirev.2020.103348.

Umgiesser, G., 2020. The impact of operating the mobile barriers in Venice (MOSE) under climate change. J. Nat. Conserv. 54. https://doi.org/10.1016/j.jnc.2019.125783.

Vaquer-Sunyer, R., Duarte, C.M., 2008. Thresholds of hypoxia for marine biodiversity. www.pnas.org/cgi/content/full/.

Vichi, M., Lovato, T., Butenschön, M., Tedesco, L., Lazzari, P., Cossarini, G., 2020. The biogeochemical flux model (BFM): equation description and user manual. In: BFM version 5.2. BFM Report series N. 1, Release 1.2.

Xu, W., Collingsworth, P.D., Kraus, R., Minsker, B., 2021. Spatio-temporal analysis of hypoxia in the Central Basin of Lake Erie of North America. Water Resour. Res. 57 (10), e2020WR027676.

Yu, X., Shen, J., Du, J., 2020. A machine-learning-based model for water quality in coastal waters, taking dissolved oxygen and hypoxia in Chesapeake Bay as an example. Water Resour. Res. 56 (9), e2020WR027227.

Zanchettin, D., Bruni, S., Raicich, F., Lionello, P., Adloff, F., Androsov, A., Antonioli, F., Artale, V., Carminati, E., Ferrarin, C., Fofonova, V., Nicholls, R.J., Rubinetti, S., Rubino, A., Sannino, G., Spada, G., Thiéblemont, R., Tsimplis, M., Umgiesser, G., Zerbini, S., 2020. Review article: sea-level rise in Venice: historic and future trends. Nat. Hazards Earth Syst. Sci. Discuss. Natural Hazards and Earth System Science. https://doi.org/10.5194/nhess-2020-351.

Zanchettin, D., Bruni, S., Raicich, F., Lionello, P., Adloff, F., Androsov, A., Antonioli, F., Artale, V., Carminati, E., Ferrarin, C., Fofonova, V., Nicholls, R.J., Rubinetti, S., Rubino, A., Sannino, G., Spada, G., Thiéblemont, R., Tsimplis, M., Umgiesser, G., Zerbini, S., 2021. Review article: sea-level rise in Venice: historic and future trends. Nat. Hazards Earth Syst. Sci. https://doi.org/10.5194/nhess-2020-351. Discuss. Natural Hazards and Earth System Science.

Zennaro, F., Furlan, E., Canu, D., Aveytua Alcazar, L., Rosati, G., Solidoro, C., Aslan, S., Critto, A., 2023. Venice lagoon chlorophyll-a evaluation under climate change conditions: a hybrid water quality machine learning and biogeochemical-based framework. Ecol. Indic. 157, 111245. https://doi.org/10.1016/j.ecolind.2023.111245.

Zollo, A.L., Rillo, V., Bucchignani, E., Montesarchio, M., Mercogliano, P., 2016. Extreme temperature and precipitation events over Italy: assessment of high-resolution simulations with COSMO-CLM and future scenarios. Int. J. Climatol. 36 (2).