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Regional ocean biogeochemical modeling challenges for predicting the effectiveness of marine carbon dioxide removal

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Effectively scaling diverse marine carbon dioxide removal (mCDR) technologies from pilot-scale demonstrations to industrial-scale deployments requires a quantitative understanding of how much additional carbon a given deployment will sequester compared to a scenario with no mCDR intervention and the long-term durability of the stored carbon. Given the high environmental variability and vast size of the ocean carbon pool, observations alone cannot resolve the amount, rate, and fate of mCDR-associated carbon sequestration. Likewise, when conducting an mCDR deployment it is impossible to observe a counterfactual scenario with no mCDR deployment performed. For this reason, ocean biogeochemical models are expected to play a key role in advancing mCDR deployments by informing observational requirements, defining uncertainty envelopes, and ultimately verifying durable carbon sequestration. However, current models, which are designed to capture basic ocean processes, have limitations when being used for this new application—simulating perturbations to the ocean system ranging in scale. Here, we describe our perspective on the most critical ocean biogeochemistry model process representations that need to be refined or added to accurately simulate the impact of a subset of mCDR approaches on carbon uptake and ocean biogeochemistry.

KEYWORDS

alkalinity, carbonate, carbon dioxide, marine, modeling, removal, reporting, verification

1 Introduction

Solving Earth's climate crisis requires simultaneous efforts to both curb anthropogenic greenhouse gas (GHG) emissions and develop scalable approaches for removing anthropogenic GHGs from the atmosphere (Lee et al., 2023). Ocean-based carbon removal solutions (Cross et al., 2023) are particularly appealing because of the vast amount of carbon stored in the world's oceans compared to the atmosphere and terrestrial landscapes, and their natural ability to buffer changes in GHG content of the atmosphere (Friedlingstein et al., 2019). Oceans contain the largest non-geological reservoir of carbon on Earth with ~37,000 Pg C present in

the form of dissolved inorganic carbon (DIC) (Keppler et al., 2020), ~700 Pg C in the form of organic carbon (Hansell and Carlson, 2014), and ~2,300 Pg C stored in the top 1 m of marine sediments (Atwood et al., 2020) compared to the atmospheric CO_2 reservoir of ~885 Pg C (Friedlingstein et al., 2019). The oceans already absorb about 25% of global anthropogenic CO_2 emissions (Friedlingstein et al., 2024) because of the ocean solubility pump (Crisp et al., 2022; Gruber et al., 2023). In general, the goal of marine CO_2 removal (mCDR) technologies is to either accelerate biotic or abiotic processes that mediate ocean carbon uptake to ultimately increase the ocean carbon reservoir or directly capture CO_2 from seawater and store it elsewhere (e.g., on land in geological reservoirs; Figure 1) (Palter et al., 2023; Rohling, 2023).

To ultimately be successful, any carbon removal technology, including mCDR, needs to reliably and transparently demonstrate the net carbon footprint of the overall process (Abdallah et al., 2012; Delacote et al., 2024). Likewise, effectively scaling mCDR technologies from pilot-scale demonstrations to industrial-scale deployments requires a quantitative understanding of how much carbon a given deployment will sequester, the fate and durability of the stored carbon, and perhaps more importantly, what potential impacts (i.e., feedbacks) large scale carbon capture will have on the Earth system and biological communities. CO_2 removal is typically quantified through domain-specific monitoring, reporting and verification (MRV) guidelines (Singh et al., 2016). MRV is geared towards quantitatively certifying carbon removal for financial carbon market purposes, and currently there is not a regulatory MRV framework in place for mCDR. Hence, emerging research-based MRV frameworks may form the basis for ocean carbon markets (Ho et al., 2023) as the technologies, our ability to monitor and model their efficiency, and carbon market regulations collectively evolve.

The primary factors that should be considered for mCDR MRV include (1) additionality (i.e., how much CO_2 is removed beyond a counterfactual baseline), (2) leakage (i.e., how much CO_2 escapes removal), (3) durability (i.e., how long the CO_2 remains sequestered), and (4) uncertainty in each of these factors (Ho et al., 2023). The relatively new field of mCDR faces three major challenges when it comes to establishing MRV. First, there are numerous different mCDR approaches being developed that harness different aspects of the ocean's carbon cycle. Second, directly measuring the impact of mCDR applications on natural cycles is impossible because of the large size and variability of the ocean carbon pool, the spatial extent over which the signal of any given mCDR application would spread across, and an inability to observe baseline conditions in a world in which no mCDR intervention was conducted. Third, quantifying the durability of sequestered carbon, particularly with respect to biotic approaches,

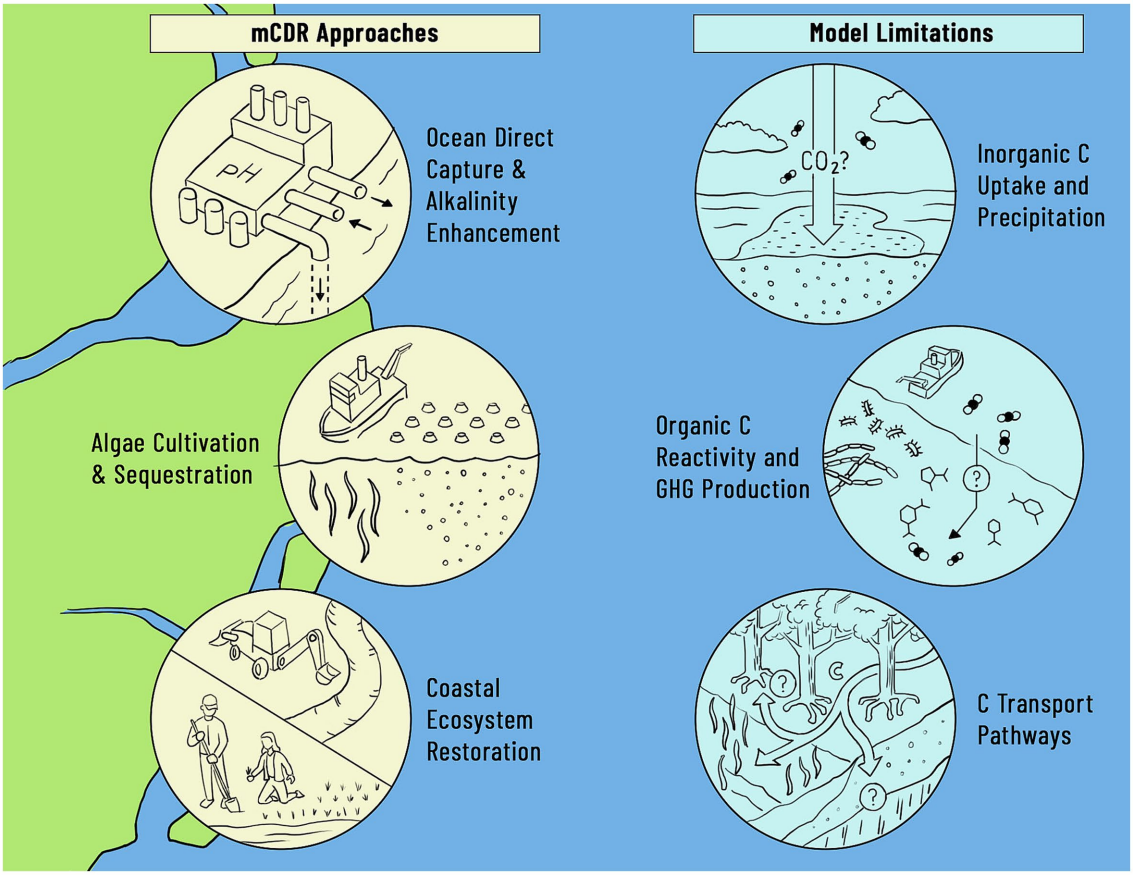

FIGURE 1
This perspective focuses on current model limitations (right) for assessing the efficacy of a subset of proposed mCDR approaches (left) that harness abiotic ocean processes for carbon sequestration (e.g., DOCCS and OAE), stimulate biotic processes (e.g., biomass sinking or enhanced micro or macro algae growth via fertilization or aquaculture), or restoration/protection of natural carbon sinks.

requires predictions of future ocean conditions and ventilation pathways. Thus, any feasible MRV framework is expected to rely on skillful numerical models with validation from observations to assess if there is a difference in ocean chemistry caused by a mCDR intervention compared to predicted counterfactual scenarios.

In terms of the first identified challenge, the scientific community and industry are exploring many diverse pathways for using the ocean to partially offset anthropogenic CO_2 emissions. These approaches generally focus on either direct capture of CO_2 dissolved in seawater for storage elsewhere (e.g., in geological reservoirs) or increasing the rate that the ocean absorbs atmospheric CO_2 and stores it in either organic or inorganic forms. A major metric of success for any mCDR technology is how long the carbon remains stored (i.e., its durability or permanence). Approaches such as ocean alkalinity enhancement (OAE) (Oschlies et al., 2023) or direct ocean carbon capture and storage (DOCCS) (Digdaya et al., 2020) primarily exploit abiotic geochemical processes that exchange atmospheric CO_2 with the marine DIC reservoir (Figure 1). At the scale of the global ocean, the residence time of DIC is nearly 200,000 years (Zeebe and Wolf-Gladrow, 2009), implying that any additional DIC uptake promoted by geochemical mCDR approaches should in theory persist in the ocean over geological time scales.

Other mCDR approaches focus on accelerating biological controls on ocean carbon storage through various pathways, including alleviating nutrient limitation for primary production (e.g., iron fertilization or artificial upwelling), directly sinking organic carbon to the marine sediment interface, or restoring and protecting natural hot spots for carbon burial (e.g., coastal blue carbon; Figure 1). The fate of biologically sequestered carbon is perhaps more challenging to determine than for carbon sequestered via geochemical approaches. Particulate and dissolved organic carbon (POC and DOC, respectively) produced in the surface ocean via photosynthesis undergoes substantial remineralization in its journey among water masses in dissolved forms and/or sinking to sediments in particulate forms. Decomposition of organic carbon in the water column is directly related to time scales of ventilation within and among water masses (Fine et al., 2017). A fraction of the organic carbon circulating throughout the water column may resist decomposition and persist over time scales of 1,000–6,000 years (Walker et al., 2016) as refractory DOC (Mentges et al., 2019), while decomposed DOC is converted to CO_2 that will degas to the atmosphere in supersaturated regions of the surface ocean or contribute to the DIC pool in undersaturated regions and potentially be entrained into the deep ocean. Likewise, carbon buried in marine sediments can persist for millions of years, however, the majority of primary production derived organic carbon sinking from the photic zone to the seafloor is decomposed before burial (Emerson, 2013).

Carbon sequestered via biotic approaches can be considered durable regardless of whether it is in the form of POC, DOC, or DIC upon remineralization so long as any of these forms of carbon remain in the ocean. Thus, the depth at which partitioning between POC, DOC, and DIC pools occurs is very important from a durability perspective given that (1) mCDR-derived carbon in the surface ocean can only be exchanged with the atmosphere if it is in the form of DIC and (2) once mCDR-derived carbon penetrates the deep ocean it is somewhat irrelevant what form it is in with respect to durability over climate-relevant time scales. Along these lines, global ocean model simulations suggest that about two thirds of the CO_2 sequestered by mCDR approaches that leverage the biological pump will leak back into the atmosphere over a 50-year timeframe (Siegel et al., 2021), though the carbon sequestration efficiency of the biological pump ranges from decades to centuries across different ocean basins (DeVries et al., 2012). One way to potentially bypass the proclivity for fresh organic carbon to be degraded in the ocean would be to recover biomass produced by biotic mCDR approaches for use as feedstock on land for diverse biomaterials that replace fossil-based components (Campbell et al., 2023; Grandgeorge et al., 2024; Campbell et al., 2025), but the resulting carbon permanence is process-specific and highly variable.

Here, we describe our perspective on the most critical ocean biogeochemistry model process representations that need to be refined or added to accurately simulate the impact of a subset of mCDR approaches on carbon uptake and ocean biogeochemistry. We primarily emphasize the challenges and opportunities for advancing regionally tuned ocean biogeochemical models to evaluate mCDR. Scaling these findings to global-scale modeling systems presents distinct challenges that merit a dedicated examination, particularly with regards to coupling mesoscale dynamics with Earth system models. Other important limitations germane to ocean modeling in general such as uncertainty in future changes in ocean circulation, the biological pump, particulate inorganic carbon cycling, and global-scale ocean carbon dynamics are not comprehensively addressed here.

2 Limitations of current models for mCDR applications

In our opinion, responsibly deploying mCDR technologies at the scale needed to tackle Earth's climate challenge (i.e., gigatons of carbon) will require robust ocean models first for gaining regulatory and societal buy-in for pilot-scale field trials, then guiding the siting of large-scale deployments, and ultimately monitoring, reporting, and verifying carbon sequestration for the sake of carbon crediting. It will be important to both use models to guide field trial design and use field trial data to validate and/or improve models. Here, we identify model gaps and biases currently limiting accurate representation of a subset of mCDR approaches.

2.1 Predicting the durability and leakage of carbon derived from biological mCDR approaches

Understanding the time scales over which carbon is partitioned between dissolved, particulate, organic, and inorganic pools in the ocean and/or returned to the atmosphere is central to any mCDR approach focused on using biology to sequester CO_2 (e.g., iron fertilization, artificial upwelling, biomass sinking, etc.). Ocean biogeochemistry models are generally based on the foundation of a nutrients, phytoplankton, zooplankton, detritus (NPZD) model that serves as the basis for predicting interplay between organic carbon production and degradation (Fasham et al., 1990). In recent decades, increasingly complex NPZD models have been developed that are capable of representing additional biogeochemical constituents (e.g., iron, phosphorus, silica, DOC), different particle size classes, more

diverse planktonic communities (Fennel et al., 2022), and coupled sediment biogeochemical processes (Moriarty et al., 2018; Rocha et al., 2018; Moriarty et al., 2021). These complexities are all relevant to the needs of emerging mCDR research and allow for more realistic predictions of when and where mCDR-derived carbon may exist as POC, DOC, or DIC. However, the computational cost of adding every one of these features to a regional or global model and running the model at an appropriate resolution to resolve these complex processes remains prohibitive (Terhaar et al., 2024). Below we discuss several areas where additional mechanistic representations could improve our capacity to predict the durability and/or leakage of carbon derived from biological mCDR approaches.

The counteracting processes of particle sinking, organic matter decomposition, and zooplankton grazing exert a primary control on the efficiency of the biological carbon pump, and, likewise the durability of mCDR-enhanced primary production, yet our ability to simulate the mechanistic drivers of these processes remains limited (Honjo et al., 2014; Boyd et al., 2019; Nowicki et al., 2022). At a molecular scale, microbes acting as the primary decomposers of sinking POC attach to particles and/or use extracellular enzymes to break down organic carbon in the form of large polymers; this both fuels the microbe's metabolism and creates lower molecular weight DOC byproducts (De La Rocha and Passow, 2007).

Models often represent the competition between POC sinking and decomposition rates (i.e., a rapidly sinking particle will have less time exposed to decomposers) based on the Martin curve, a power law function to compute POC flux as a function of depth in the water column and a remineralization parameter (Armstrong et al., 2001; Williams and Follows, 2011). More complex representation of individual particle characteristics (e.g., mineral ballast, size specific degradation rates) have yielded additional insight into the drivers of the ocean biological pump (Armstrong et al., 2001; Buesseler and Boyd, 2009; Omand et al., 2020). However, experimental results have challenged the assumption that particle sinking and remineralization rates are independent. The physical act of sinking, the rate of which is a function of suspended solids in the water column (Turner et al., 2021), has been shown to increase POC degradation rates as these breakdown products are shed from the main particle, eliminating enzymatic competition (Alcolombri et al., 2021). Vertical zooplankton migration is another process that may play an outsized but poorly understood role in the fate and durability of sinking POC (Archibald et al., 2019). For example, larger zooplankton that more actively migrate up and down in the water column have been shown to transport twice as much carbon from surface to deep waters than smaller, less migratory organisms (Hansen and Visser, 2016). Microbially-explicit models also exist that are capable of resolving both zooplankton migration (Morozov and Kuzenkov, 2016) and microbial community interactions with individual particles that change both microbial abundance and particle properties as they sink (Nguyen et al., 2022). Representing these processes at the scale of individual algae blooms may be an important tool for evaluating the durability of some biotic mCDR applications such as iron fertilization.

Biogeochemical transformations that occur once POC reaches marine sediments via natural or human-induced sinking play a key role in determining potential leakage and the overall impact of biotic mCDR applications on atmospheric global warming potential. Benthic production of other GHGs such as methane (CH_4) and nitrous oxide (N_2O) is a potential leakage pathway that can potentially minimize the amount of global warming potential removed from the atmosphere, which may be important for models to consider in some cases (e.g., when deliberately sinking biomass). CH_4 and N_2O are substantially more potent, albeit shorter lived, GHGs compared to CO_2 with 20 year sustained global warming potentials of 96 and 250 times that of CO_2, respectively (Neubauer and Megonigal, 2015). Coastal and marine environments can act as either sources or sinks of both CH_4 and N_2O depending on the balance between production and oxidation in sediments and the water column (Canfield et al., 2005; Foster and Fulweiler, 2016). Globally, the oceans act as a source of both GHGs to the atmosphere (Tian et al., 2024; Saunois et al., 2025). In relation to biological mCDR approaches, the composition and abundance of organic matter plays a direct role in mediating sediment CH_4 (Valentine, 2011) and N_2O production (Eyre et al., 2013). To ensure that mCDR approaches that modify seafloor carbon content do not end up replacing atmospheric CO_2 with other more potent GHGs it is important to evaluate how the goal of organic carbon storage in anoxic environments influences production of other GHGs and whether produced GHGs are oxidized in the water column or emitted to the atmosphere. As previously mentioned, detailed models exist that can incorporate sediment dynamics (Fennel et al., 2006; Lee et al., 2022) into ocean biogeochemistry models as well as CH_4 and N_2O cycling in the water column (Buitenhuis et al., 2018; Żygadłowska et al., 2023), but there remains large uncertainty around parameterizing such models and our basic understanding of the interplay between aerobic and anaerobic processes mediating CH_4 and N_2O fluxes.

Many discussions of the carbon sequestration potential of biological mCDR focus on the efficiency of POC burial in sediments. The intricacies of DOC cycling in the water column are also important to consider from both carbon accounting and ecosystem impact perspectives considering DOC is the foundation of aquatic food webs. Some ocean biogeochemistry models define two pools of DOC—labile and refractory—that turnover on timescales from hours to days and millennia, respectively (Khangaonkar et al., 2021). In a mCDR context, refractory DOC could be described as "more durable," whereas labile DOC could be substantially "leakier" if degraded in surface waters where atmospheric CO_2 exchange can occur. Some models such as Carbon, Ocean Biogeochemistry and Lower Trophic version 2 (COBALT v2) designed for global implementations and the Estuarine Carbon Biogeochemistry (ECB) model designed for estuarine conditions in settings like the Chesapeake Bay (Feng et al., 2015) have an additional pool of semi-labile DOC (Stock et al., 2020). In reality, DOC exists across a much wider spectrum of reactivities, which are generally classified as labile, semi-labile, refractory, or ultra-refractory (Hansell, 2013), but even these classifications are an oversimplification.

Roughly half of the global ocean's net primary productivity is cycled through a pool of highly reactive DOC (i.e., metabolites) on the order of minutes to days, which represents a miniscule pool (<0.1% of total DOC) but a massive flux (15–25 Pg C $yr.^{-1}$) (Moran et al., 2022a). The byproduct of labile DOC cycling is not simply CO_2; microbial processing generates chemically complex molecules that comprise the pool of recalcitrant DOC in the ocean (Moran et al., 2022b). Further complicating matters, the reactivity of a given molecule is not necessarily related solely to its chemical structure (Zonneveld et al., 2010; Ward et al., 2017). Processes such as priming effects (Bianchi et al., 2015; Ward et al., 2019) and photo-oxidation (Stubbins et al.,

2012; Ward et al., 2014) can amplify the reactivity of semi-labile or refractory molecules under certain conditions, which should be considered when assessing the additionality of biotic mCDR interventions. From a modeling perspective, there has been recent progress that explicitly tracks concentrations of ~100 distinct molecules in response to interactions with ~35 unique microbial units; even when assuming that each class of molecules has equal reactivity, the model was capable of generating distinct pools of labile and refractory DOC (Mentges et al., 2019). Other relevant advances have been made in terrestrial reactive transport models that define varying levels of organic carbon reactivity based on ultra-high resolution mass spectrometry data (Muller et al., 2024).

In summary, the durability of biologically sequestered carbon in the ocean depends on complex interactions between particle sinking, organic matter decomposition, zooplankton grazing, sedimentary processes, DOC cycling, and ocean circulation, all of which influence potential leakage of CO_2 and other GHGs like CH_4 and N_2O to the atmosphere. While biogeochemical models have advanced significantly in representing these processes, limitations remain in simulating microbial dynamics, particle properties, and sedimentary transformations. An ability to accurately predict when and where organic carbon is remineralized, which requires models to be skilled at simulating both organic carbon remineralization and large scale ocean currents (e.g., DeVries et al., 2012; Siegel et al., 2021), is a central modeling capability for biotic mCDR approaches considering that whether organic carbon is remineralized to DIC in surface versus deep waters can influence the time scales over which mCDR-derived carbon is durable by several orders of magnitude.

2.2 Predicting the efficiency of inorganic carbon sequestration

Model and observation-guided MRV strategies for mCDR approaches that harness abiotic geochemical processes to sequester CO_2 in the form of DIC are perhaps more tractable compared to biotic approaches considering the thermodynamics of the marine carbonate system are thoroughly understood (Stock et al., 2014; Aumont et al., 2015) compared to the microbial physiology and ecology mediating DOC transformations. Likewise, in comparison there is a fairly small number of tracers needed for MRV with geochemical approaches–e.g., pH, the partial pressure of CO_2 (pCO_2), DIC, and total alkalinity (TA)–as opposed to the hundreds of thousands of currently uncharacterized organic molecules in the ocean that contribute to a vast array of coupled biogeochemical cycles (Moran et al., 2022b). The high temporal variability in carbonate cycle parameters, particularly near the coast, and sheer size of the DIC pool in the ocean drives a need for extremely precise and spatiotemporally resolved observations to capture signals of geochemical mCDR, hence the need for reliable predictive capabilities for MRV (Schulz et al., 2023; Wang et al., 2023). The efficiencies of geochemical mCDR approaches are limited in multiple respects, driven by uncertainties in the response of alkalinity additions (and other mCDR approaches) in different environments, the complexity of biogeochemical and ecosystem feedbacks on the implementation of mCDR approaches, and our inability to accurately simulate these processes. MRV for DOCCS approaches (Aleta et al., 2023) benefit from the fact that the collected CO_2 can be directly quantified, however, these technologies often result in discharge of elevated pH water and thus share some modeling challenges with OAE. This section focuses primarily on OAE for this reason.

Although carbonate system representation can widely vary between different modeling studies, the standardized Ocean Model Intercomparison Project (OMIP) protocols provide guidance that, at a minimum, TA should require representation of CO_2, carbonate, bicarbonate, hydroxide and hydrogen ions, and borate (Orr et al., 2017), while additional contributions of silicon and phosphorus alkalinity can be computed offline. Many global ocean models also represent changes to TA over coarse spatial scales and relatively large time steps, well past the time necessary for equilibration of added alkalinity products. In contrast, the representation of the carbonate system in regional models is generally much more diverse with respect to the complexity of simulated dynamics (Shen et al., 2019; St-Laurent et al., 2020; Hauri et al., 2021). At a minimum, biogeochemical simulations represent a simplified version of carbonate chemistry that mechanistically simulates TA as a function of salinity and can be adjusted by processes of nitrification and denitrification (Fennel et al., 2008).

More complex ecosystem models such as COBALT (Stock et al., 2014; Stock et al., 2020) coupled to Regional Ocean Modeling System (ROMS; Shchepetkin and McWilliams, 2005) add complexity to carbonate system representation by allowing TA and DIC to be directly affected by both physics and biogeochemical reactions (Hauri et al., 2020). Mechanistic models such as Eco3M (Baklouti et al., 2006; Baklouti et al., 2021), further link the carbonate system to processes such as explicit remineralization by bacteria and the reactivity of labile, semi-labile, and refractory carbon pools along with different detritic pools, and have been deployed in multiple regions including the Mediterranean Sea (Pagès et al., 2020a; Pagès et al., 2020b; Lajaunie-Salla et al., 2021) and the tropical Pacific (Gimenez et al., 2018). However, such models are computationally expensive and difficult to evaluate since they involve parameters that are less frequently measured in tandem with carbonate system parameters (e.g., different pools of DOC, cellular abundance).

There are a variety of regionally heterogeneous factors that could either substantially limit the efficacy of mCDR approaches for a given region and/or increase the uncertainty of predictions for a given region. In terms of factors limiting efficacy, potential interactions between alkalinity feedstocks with sediment and organic particles, which are generally more abundant in coastal systems (and closer to the sea surface in the case of sediments) compared to the open ocean, could reduce the overall efficiency of CO_2 uptake associated with OAE. Coastal regions exhibit highly heterogeneous particle concentrations throughout tidal cycles, seasons, and following passage of storms (McAnally William et al., 2007; Green and Coco, 2014). There are also potential additionality concerns from interactions between OAE with natural sources of alkalinity in shallow marine sediments (Bach, 2024). Despite these concerns, deploying OAE in coastal settings is desirable from logistical, regulatory, and MRV perspectives (Oschlies et al., 2023), meaning substantial effort should be made to enhance process-based predictive capacity for diverse coastal regions.

From our perspective, among the potentially most important model gaps to resolve with respect to geochemical mCDR approaches (i.e., OAE and effluent from DOCCS) are how the following processes behave when pushing the carbonate system to extremes not typically observed in nature: mineral precipitation and sinking dynamics, gas

exchange, and the influence of initial carbonate conditions on system responses along with the absence of feedback effects from the carbonate system on organisms (i.e., organisms are not influenced by the carbonate system). Some of these gaps are not due to a lack of process representation in models, per se, but rather are associated with challenges in parameterizing models for conditions that the ocean does not typically experience (e.g., large local pH and TA shifts). On the other hand, mineral precipitation and feedback between the carbonate system and organisms lack representation in current biogeochemical models.

Traditionally, there has not been a need to focus much effort on high pH mineral precipitation. However, precipitation of minerals such as brucite, which happens rapidly during initial alkalinity addition, or calcium carbonate, which occurs more gradually, effectively remove the additional alkalinity from the system if these precipitates sink (Hartmann et al., 2023). In the worst case scenario, runaway precipitation can occur when aragonite saturation exceeds a specific threshold (Moras et al., 2022), which would negate any carbon sequestration benefits of OAE, and potentially contribute to reduced CO_2 uptake relative to typical levels. In this worst-case runaway precipitation scenario, any CO_2 emissions associated with the OAE technology would not be offset by the intended benefits. Thus, we argue that representing precipitation in models is essential from an MRV perspective for OAE technologies operating at or near potential precipitation thresholds.

In terms of air-sea gas exchange, the typical wind and concentration gradient based equations used in ocean models (Wanninkhof, 2014) reliably capture the dominant driver of gas exchange–high winds. However, we argue that chemical enhancement of gas exchange (i.e., hydration reactions of CO_2 with water and hydroxide ions) may also be important to consider when modeling OAE scenarios (Wanninkhof and Knox, 1996). Limited experimental results suggest that chemical enhancement may account for up to 8% of total gas exchange under low wind conditions (Wanninkhof and Knox, 1996). Such processes may be even more impactful with larger pCO_2 gradients and low turbulence conditions; for example, pCO_2 can approach 0 ppm at a pH of 9 (Ringham et al., 2024), which is a common maximum pH for the types of discharge permits many OAE practitioners are pursuing in the US. Waves are also often not considered but models such as Wave Watch III exist that could be coupled to ocean biogeochemistry models (Bi et al., 2015). These challenges are relevant to both OAE in general as well as many DOCCS approaches, which often have some element of alkalinity addition (e.g., elevated pH effluent after removing CO_2 from seawater).

2.3 Predicting global impact of ecosystem restoration and protection

Predicting the effectiveness of restoring and/or protecting natural ecosystem functions that efficiently sequester carbon, often referred to as nature based solutions (Buma et al., 2024), shares many modeling challenges with the biotic mCDR approachesdiscussed above. The majority of proposed marine restoration-based approaches would involve organic carbon cycling in some way with the trophic level of interest ranging from zooplankton (Luo et al., 2020), to macroalgae (Queirós et al., 2019) and corals (van der Heijden and Kamenos, 2015), up to the scale of fisheries (Saba et al., 2021) and macro-fauna (e.g., whales) (Pershing et al., 2010). As such, assessing the durability of carbon sequestration associated with these restoration-based methods will rely on addressing many of the same modeling challenges described for engineered biotic mCDR approaches. The challenges identified for geochemical approaches are perhaps less impactful for understanding restoration-based mCDR considering such approaches would not push marine ecosystems to new extremes but rather focus on restoring balance to natural processes and mitigating human influence. In addition to microscale refinement in models, restoration-based mCDR focused on fauna may also require more detailed coupling of ocean biogeochemistry, fisheries (Cheung et al., 2010; Marshall et al., 2017), biodiversity (Cheung et al., 2009), and social models (Kasperski et al., 2021) to assess additionality. For example, changes in fishery practices (e.g., decreased harvesting) in one region may promote increased harvesting in another (Cross et al., 2023).

Restoring and protecting "blue carbon" habitats (e.g., marshes, mangrove, and seagrass) is another prominent mCDR strategy due to high rates of carbon burial compared to terrestrial and open ocean systems (McLeod et al., 2011). Robust predictive capacity for assessing carbon burial in these ecosystems such as the marsh equilibrium model exist (Vahsen et al., 2024). However, a lack of representation of coastal vegetated ecosystems in Earth system models prevents us from assessing additionality of restoration-based solutions when interacting with the broader Earth system (Ward et al., 2020). Likewise, models focused on floodplain dynamics typically use surface water environments as boundary conditions (Yabusaki et al., 2020; Sulman et al., 2024), but do not explicitly focus on connecting material fluxes to ocean models. This may be particularly important in the context of restoring coastal habitats given the largest uncertainty in their ability to sequester carbon is how much carbon and alkalinity are exported laterally from the coastline to the open ocean (Santos et al., 2021).

While restoration-based mCDR may not be the most economically viable in terms of cost per ton of CO_2 (Williamson and Gattuso, 2022), it is likely among the most socially acceptable first steps to take given the undeniable co-benefits such as improving habitat for fisheries and buffering of coastal flooding among others (Gattuso et al., 2021).

2.4 General considerations for modeling mCDR interventions

Additionality is generally assessed by comparing the difference in net atmospheric CO_2 uptake between simulations of an mCDR intervention and its counterfactual scenario (Oschlies et al., 2025). This approach of subtracting results of one simulation from another inherently differentiates natural variability from mCDR-induced changes over the modeled domain assuming the mCDR intervention is represented in a way that does not alter ocean physics. For example, when simulating alkalinity release from a wastewater treatment plant, Khangaonkar et al. (2024) only introduced alkalinity to the model domain without altering the transport of mass and heat, which would alter physical circulation and make each scenario incomparable.

To be useful for this application, models need to be skillful enough to accurately represent physical, biological, and chemical processes within the spatial domain of interest. For example, issues with accurately representing ocean circulation may in some cases exert substantial uncertainty (Fox-Kemper et al., 2019). Likewise, while regional ocean biogeochemistry models generally do a good

job of capturing large scale trends, they have a hard time capturing patchy or episodic processes like localized algae blooms, leading to mismatches between modeled and observed carbonate system concentrations (Shen et al., 2019). Model skill is generally assessed through a series of validation and sensitivity analyses and can be improved using statistical data assimilation techniques (Rothstein et al., 2015; Fennel et al., 2022). However, data assimilation for mCDR applications has some unique challenges. First, it is impossible to make observations of the counterfactual condition (Ho et al., 2023; Fennel, 2024). Second, by assimilating carbonate system data into simulations of the mCDR intervention, the counterfactual simulation is no longer comparable; however, it is perhaps feasible to assimilate data types not impacted by the intervention such as salinity or dissolved oxygen (Fennel et al., 2023).

Because multiple scenarios need to be compared to assess additionality, sources of numerical noise should also be evaluated to confirm that differences between the counterfactual and mCDR simulations are indeed due to the mCDR intervention. Model noise can interfere with accurately capturing key processes like the additionality of OAE or other mCDR interventions. It has long been understood that modeling is susceptible to numerically induced artifacts due to methods used to solve equations (Walters and Carey, 1984). Representing continuous processes through discrete operators inevitably leads to approximation and truncation errors. Despite significant advancements over the years to reduce such artifacts, particularly in areas like advection (Adcroft et al., 2019) and spurious mixing (Holmes et al., 2021), numerical noise continues to be a central issue in ocean modeling. Numerical noise is influenced by various factors, such as the advection scheme, time step, grid size, compilation options, and hardware configuration. Understanding these influences is critical for improving model accuracy. Careful evaluation of each model and domain is essential to ensure that observed changes in pCO_2 are due to an mCDR intervention rather than numerical noise.

A significant source of noise also arises from the intrinsic conceptual model used to represent biogeochemistry in ocean models. Indeed, biogeochemical models are based on different assumptions that can affect the end results. In the case of COBALT v2, for example, weak feedback between chlorophyll and TA exists, arising from the fact that the saturation state impacts the production of aragonite and calcite detritus, which in turn will impact export. Therefore, even a small change (in the case of an OAE experiment, for example) will set the model off on a slightly different trajectory, leading to different mesoscale and submesoscale realizations very quickly. This issue has been overcome in the latest version of COBALT (Stock et al., 2024) by reading chlorophyll-a from a file, cutting the link between TA and chlorophyll-a and reducing that source of noise. This specific issue highlights the importance of deeply investigating, understanding, and minimizing sources of model noise when using models for MRV.

Ultimately, the purpose of a particular model experiment should drive the level of realism and skill required from a given model configuration (Fennel et al., 2023) as the mCDR field evolves from idealized simulations focused on proof of principle and hypothesis testing (Köhler et al., 2013; Keller et al., 2014) to more realistic simulations of anticipated or actual field trials and commercial deployments (Wang et al., 2023; Khangaonkar et al., 2024; Guo et al., 2025; Laurent et al., 2025).

3 Solutions for refining ocean models for mCDR

Here we provide a road map with several tangible solutions for improving computational approaches to better support predictions and/or verification of the permanence of carbon stored in the ocean as a result of mCDR interventions. Recommendations by Fennel et al. (2023) on critical processes that need improved model representation, validation, and uncertainty quantification lay the groundwork for the solutions we propose as potential first steps, which include (1) expanding efforts to experimentally and observationally refine parameterization of fundamental ocean processes that play an outsized role in assessing proposed mCDR interventions, (2) establishing a modular approach for incorporating improved representation of processes specific to the MRV needs of different mCDR technologies in an ensemble of models, and (3) defining and testing criteria for traceable and auditable uncertainty quantification for models used for MRV across a range of ocean conditions.

3.1 Lab to field scale parameterization and validation

Insufficient observational data and process studies to support ocean biogeochemical model development is a central challenge facing the oceanography community. This challenge is further amplified when using existing models for new applications like mCDR. Large scale coordinated research programs like Export Processes in the Ocean from RemoTe Sensing (EXPORTS) play a critical role in providing the foundational data needed for developing next generation ocean models (Bisson et al., 2018; Archibald et al., 2019; Kramer et al., 2022; Pinti et al., 2023). However, at this early stage in mCDR research, even relatively modest investments in laboratory and field experimentation can yield critical insight for how to better use existing models for mCDR applications (Cyronak et al., 2023; Iglesias-Rodríguez et al., 2023; Riebesell et al., 2023; Savoie et al., 2025).

A major challenge when using existing models for mCDR is that current model parameterizations have typically not been designed to capture the extremes that mCDR applications will produce (e.g., highly localized pH changes or organic matter loading). Refining process representation and parameterization in ocean biogeochemistry models for both biotic and geochemical mCDR approaches can benefit from idealized model development informed by lab scale experimentation focused on parameterizing rates (e.g., carbonate system equilibration, organic carbon reactivity). For example, using a model that only simulates the carbonate system and air-sea exchange is likely the most tractable approach for building in new capabilities such as representation of brucite/carbonate precipitation thresholds when introducing concentrated alkalinity to seawater. In many cases, highly controlled beaker to bottle-scale experiments may be needed to build and test idealized models of a specific process, following guidelines established for OAE best practices (Iglesias-Rodríguez et al., 2023). Then, linking small-scale processes to realistic feedbacks in regional models will require rigorous testing of biogeochemical parameterizations at the mesocosm scale to help reduce the web of

complex uncertainties that will be introduced as numerical experiments and mCDR deployments are implemented in realistic coastal ocean domains.

Experimental approaches can test and measure CO_2 uptake, organic matter decomposition and other carbon related processes across multiple different physico-chemical treatments (e.g., salinity, temperature, and TA) and mCDR approaches (e.g., different sources of alkalinity, biological communities that are stimulated by fertilization, and different forms of biomass that are buried). Gradually increased complexity in mesocosm experiments can help determine other effects like CO_2 exchange that may be affected by processes like chemical enhancement (Wanninkhof and Knox, 1996). Isolated mesocosms can be made increasingly complex to incorporate different model elements such as sediment, particles, and flora/fauna (Zayas-Santiago et al., 2020) and ultimately controlled floating infrastructure (Riebesell et al., 2013; Riebesell et al., 2023). In terms of OAE, validation of carbonate dynamics for multiple different alkalinity types in the lab or mesocosms can then help bridge the gap to field-scale experiments in more complex environments with substantially higher natural variability and confounding factors. For example, how do different proposed OAE feedstocks interact with diverse initial conditions to drive gas exchange and additional DIC uptake? Likewise, how does the reactivity of organic matter associated with different types of proposed biotic mCDR approaches (e.g., microalgae, macroalgae, wood, etc.) vary under diverse environmental conditions and stimulate or repress production of other GHGs? As we seek to refine our models for mCDR applications, diverse types of experimental data (collected from lab benches as well as on beaches and in bays, and oceans) will be essential for testing these refinements.

3.2 A modular approach for mCDR-specific model improvements

Connecting regional ocean models to finer spatial-scale processes will bring forth a multitude of complicating factors, not least of which is increased computational demand. When modeling more realistic field conditions, simulating biogeochemical responses to alkalinity additions and/or primary production will require more complex representations and/or parameterizations of processes involving carbonate dynamics, concentrations of elements that are typically considered stable (e.g., Mg and Ca), those toxic to phytoplankton (e.g., Ni) (Fennel et al., 2023), and a more realistic representation of organic matter reactivity beyond labile, semi-labile, and refractory (Muller et al., 2024), among other factors. Smaller spatial-scale dynamics will also be required to simulate the potential for secondary precipitation, particle sinking rates, subduction of highly alkaline surface waters to subsurface waters with less chance for atmospheric contact, air-sea exchange rates (Fennel et al., 2023), and interactions between sinking POC and planktonic communities. Additionally, capturing carbonate equilibrium or pulses of nutrients or organic matter in an energetic marine environment is imperative before a plume is diluted and exported out of a regional model domain. Tracking the extent of an exported plume with undersaturated pCO_2 may then require another connection between a regional model with higher complexity and a global model with simplified representations of carbonate and organic matter cycling dynamics as the air-sea gradient equilibrates over longer time scales.

Several logistical hurdles remain for implementing such complex biogeochemical dynamics within regional modeling systems, each with benefits and tradeoffs. The implementation of the same biogeochemical model (e.g., ECB, COBALT, PISCES, ERSEM, among others) (Fennel et al., 2019) across multiple domains offers a high degree of control over numerous variables and parameters and would reduce uncertainty in the biogeochemical responses of mCDR efforts due to varying model configurations. But importing an unfamiliar biogeochemical component into a mature regional ocean model will also likely necessitate extensive calibration, potentially including key model processes that lack experimental or observational data for model validation. Alternatively, individual users with well-validated and individualized biogeochemical parameterizations for their regional ocean models can apply significant expertise and professional judgment when implementing code changes that incorporate additional complexity for specific processes like carbonate system or organic matter cycling dynamics in their region of study. Yet this approach would also require significant, voluntary effort on the part of a wide array of users to maintain updated representations of known biogeochemical responses to mCDR activities in a rapidly expanding research field with a nascent set of standards and best practices (Oschlies et al., 2023).

One promising approach involves adding processes through coupled modules (Figure 2) that are transferable across models and regions. This approach would alleviate the need for individual researchers to make mCDR-specific modifications by either directly altering the code underlying their existing well-calibrated models and/or changing to a different biogeochemical configuration used by others in the mCDR modeling community. The outcome of mCDR-specific module couplings is more robust predictions of optimal dispersion methods and Earth system feedbacks in regions to which models are well calibrated. The concept of adding model functionality with model couplers and/or modules is a common approach (Jöckel et al., 2005), but has not been applied to mCDR applications, specifically. For example, Régimbeau et al. (2025) modified representation of phytoplankton physiology in global Earth system models based on genome level models to better understand how bioavailable metabolites influence DOC cycling.

We propose that a hybrid approach capable of integrating with varying levels of biogeochemical complexity may be best suited for widespread use and the adoption of regular standards that will benefit model comparability efforts. Such an approach would allow users to maintain customized code for their region of interest while utilizing a coupler (e.g., a software component that facilitates data exchange and synchronization between distinct model components) to connect a separate mCDR module that adaptively responds to relevant variables in the native biogeochemical configuration. This mCDR focused module would then benefit from community input, with potential for full-time support to document and archive validated parameters in a central module repository which reflects the latest scientific understanding based on lab and field experiment results. For members of the ocean modeling community interested in engaging in mCDR research for the first time, the existence of mCDR specific modules would reduce the upfront effort and cost of modifying their model of choice with mCDR specific considerations. In contrast, developing increasingly detailed and bespoke biogeochemical parameterizations for different regional modeling domains may be a time-intensive and potentially error-prone process, with an end result that would make

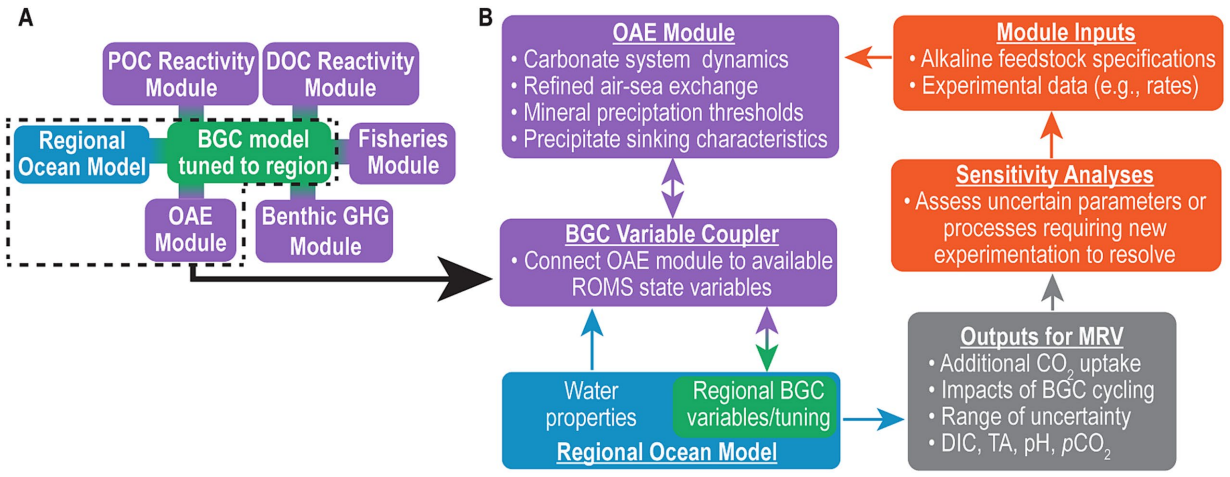

FIGURE 2
(A) A modular approach for adding complexity and process richness to biogeochemical (BGC) models tuned to specific regions is one potential solution for addressing the mCDR-specific model limitations discussed in this paper. Rather than building every possible piece of functionality into one model, users could select which modules are needed for specific mCDR approaches. **(B)** An example of how to couple an OAE-specific module (purple) with general regional ocean circulation models (blue) and their biogeochemical component (green), the relevant outputs needed for MRV (gray), and iterative improvements that can be made to the module through regional sensitivity analyses and new experimentation (orange).

performing side-by-side comparisons of mCDR dynamics increasingly challenging. A modular approach to improved biogeochemical process representation may also allow for faster, more transparent implementation among users who can continue to operate with a well-validated model configuration and add additional mCDR-specific complexity as they see fit.

It is worth noting that coding new processes is only the first step in a much longer model development process requiring extensive validation against field observations, sensitivity analysis, and iterative refinement—all of which require substantial observational data that is largely unavailable for many mCDR-specific processes. Likewise adding more complexity to a model purely for the sake of more detailed process representation is not always useful, and over-parameterization is a risk (Schneider et al., 2017). Before embarking on model modifications it is useful to think through the types of questions posed by Martin et al. (2024) such as "are data available to assess the impact of including the process?"

3.3 Leveraging distinct regions to test transferable mCDR-specific model improvements

Developing mCDR-specific modules that improve regionally tuned biogeochemical models will require testing and parameterizing them across distinct estuarine, coastal, and ocean settings to understand when and why existing models may be biased or uncertain when used for mCDR applications. For example, global simulations have shown that the efficiency of carbon uptake following alkalinity addition can vary by 10% or more across different ocean basins depending on both the physical dispersal and transport of alkalinity and initial carbonate system conditions (Burt et al., 2021). At the scale of specific coastal regions, the types of modular mCDR-specific parameterizations we propose in Section 3.2 may also have varying influence on overall model skill depending on the region. For example, in more sheltered or lower wind regions, the current common assumption that gas exchange does not occur during no to low wind conditions will likely exert substantially more bias than for a high wind region or the open ocean. Likewise, accurately representing secondary mineral precipitation is likely most important when simulating OAE in regions with higher baseline aragonite saturation.

Here, we discuss how the distinct characteristics of three prominent coastal regions in the United States—the Pacific Northwest Coast, Chesapeake Bay, and Gulf of Alaska—may facilitate valuable tests for OAE-specific modules based on their differences and similarities. We specifically highlight coastal environments instead of major ocean basins because many early field trials and commercial deployments are most likely to be conducted nearshore for practical reasons (e.g., access to existing infrastructure and energy). Comparing gains or losses in model skill when applying new parameterizations to these and other regions will begin to highlight key uncertainties in existing models for mCDR applications and improve module interoperability with models of varying biogeochemical complexity.

The Pacific Northwest Coast is an eastern boundary upwelling region (Hickey, 1979) characterized by high spatial and seasonal variability in carbonate conditions (Figure 3A). This region is characterized by anomalously high primary production during the summer (Ware and Thomson, 2005) despite relatively weak upwelling winds compared to the northern California coastline (Hickey and Banas, 2008). Upwelling delivers nutrient-rich, low oxygen, and high pCO_2 water onto the shelf, which supports high primary production but creates challenges such as coastal acidification and hypoxia (Feely et al., 2008; Feely et al., 2010; Davis et al., 2014; Murray et al., 2015; Siedlecki et al., 2015). High DIC water entering the Salish Sea through intense estuarine exchange flow (MacCready et al., 2021) also leads to net outgassing of CO_2 from water to air (Murray et al., 2015; Jarníková et al., 2022), although in-gassing can also be significant in particular locations throughout the year. From a modeling perspective, these conditions create opportunities to test the efficiency of mCDR approaches under highly variable pCO_2 gradients, ranging from highly

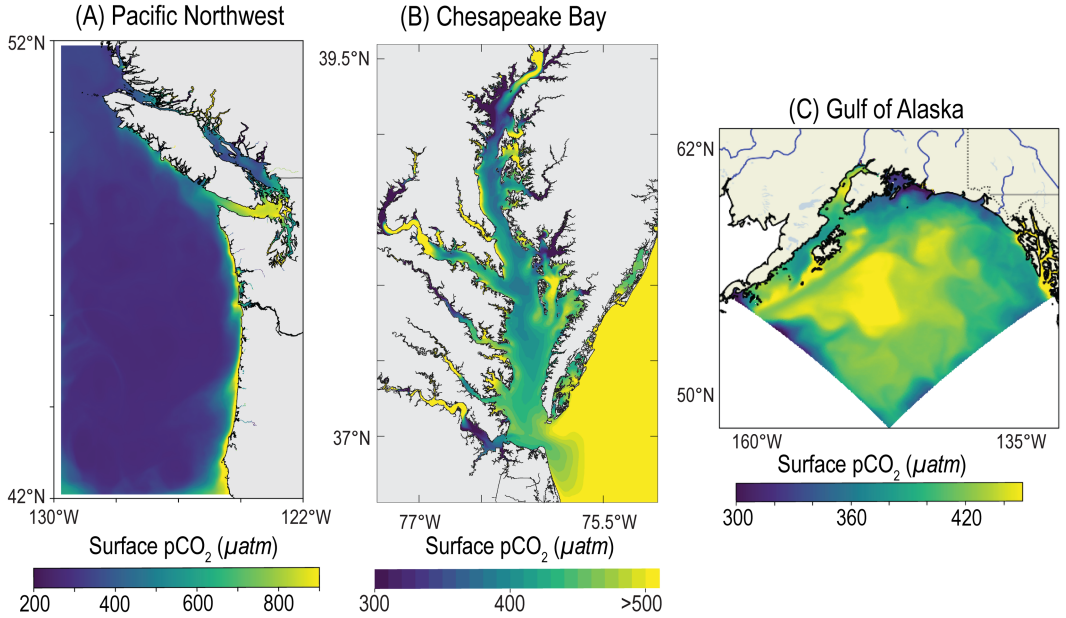

FIGURE 3
Simulated surface pCO_2 for the summer of 2016 (July, August, September) in **(A)** the Salish Sea and Pacific Northwest Coast (MacCready et al., 2021), **(B)** the Chesapeake Bay (St-Laurent et al., 2020; Da et al., 2021; St-Laurent and Friedrichs, 2024), and **(C)** the Gulf of Alaska (Hauri et al., 2024). The unique biogeochemical behaviors in these three major coastal regions exemplify the type of diverse systems we propose testing new mCDR-specific modeling capabilities. Note that the color scale shows all values greater than 500 µatm as yellow for panel C since very high pCO_2 values are found at the outfall of some rivers. Data presented in this figure is available from Pagès et al. (2025).

supersaturated to undersaturated conditions. For example, one could test if there are efficiency losses or gains when using OAE to lower natural CO_2 outgassing in supersaturated locations instead of promoting additional CO_2 uptake. Likewise, one could test new gas exchange parameterizations to understand potential biases in predictions of efficiency under different initial pCO_2 conditions.

In contrast to the Pacific Northwest Coast, Chesapeake Bay offers a test environment shaped by terrestrial inputs, shallow estuarine depths, partial haline stratification driven by microtidal dynamics, and relatively limited estuarine exchange flow (Feng et al., 2015). Freshwater and nutrient inputs related to eutrophication across the region drive seasonal spring blooms with exceptionally undersaturated pCO_2 conditions (<300 µatm) compared to near atmospheric pCO_2 conditions throughout the rest of the year (Figure 3; Da et al., 2021; St-Laurent and Friedrichs, 2024). TA varies from <300 µmol kg^{-1} in freshwater reaches to >2,000 µmol kg^{-1} closer to the ocean, highlighting the influence of terrestrial inputs on carbonate system dynamics unique to river-dominated estuarine systems. The Chesapeake Bay provides an important counterpoint to the high energy Pacific Northwest Coast due to the Bay's relatively constrained exchanges with the ocean across its mouth that reduce the influence of winds and upwelling and the short residence times (2–3 months in individual tributaries) (Shen and Haas, 2004). Testing OAE simulations in the microtidal, shallow, and partially stratified Chesapeake Bay environment would effectively extend the range of conditions in which an OAE module will have to perform, and, in comparison to the Pacific Northwest Coast, test whether parameterizations developed in energetic upwelling regions can capture the subtleties of stratified environments with weaker circulation dynamics.

Finally, we turn to the Gulf of Alaska, where production is driven by contrasting upwelling and downwelling regimes. The Gulf of Alaska exhibits yet another layer of complexity, offering a productive shelf ecosystem influenced by both cyclonic offshore upwelling and coastal downwelling (Stabeno et al., 2004; Weingartner et al., 2005; Hauri et al., 2021; Hauri et al., 2024). Summertime primary production and low salinity drive undersaturated pCO_2 conditions, a stark contrast to high pCO_2 conditions found in Pacific Northwest upwelling zones (Figure 3C). The region's relatively low carbonate concentrations (Bednaršek et al., 2021) may also help mitigate the risk of secondary precipitation during alkalinity addition and provide a low carbonate endmember compared to the other regions. Evaluating how sensitive the three different regions are to thresholds for precipitation will be useful for understanding whether generalized versus region-specific parameterizations are suitable. Furthermore, the cyclonic circulation disperses low-pCO_2 waters into the Arctic Ocean (Méheust et al., 2013), suggesting broad downstream effects from localized mCDR deployments in this region. By modeling mCDR in the Gulf of Alaska, we can test how physical transport of alkalinity and DIC over long distances impacts carbon sequestration efficiency and durability, providing insights transferable to other subpolar or Arctic settings that are expected to be highly efficient from an OAE perspective (Zhou et al., 2024).

The Pacific Northwest Coast, Chesapeake Bay, and Gulf of Alaska collectively embody large gradients in circulation, carbonate chemistry, sediment interactions, and nutrient dynamics. By leveraging the distinct characteristics of these regions, along with other regions with established and well-calibrated biogeochemical models, we can accelerate development of transferable improvements of mCDR-specific model parameterizations and process

representation. Comparing model performance across regions with varying carbonate and circulation dynamics will allow the mCDR community to mitigate biases, optimize parameterizations, and refine uncertainty quantification frameworks.

4 Outlooks and conclusions

In this manuscript, we summarize our current perspective on limitations of current regional ocean biogeochemistry models for mCDR applications and offer a roadmap for incorporating mCDR-specific model improvements with a modular approach. We argue that these types of model improvements are needed to support early efforts to scale up from small pilot field trials to commercial deployments, and ultimately to large enough mCDR interventions that move the needle in terms of climate change mitigation. Advancing across these scales will require decadal vision and highly coordinated rather than siloed research and mCDR technology deployment endeavors.

The implementation of mCDR efforts with spatially wide-reaching effects due to, for example, slow air-sea CO_2 equilibration times could provide substantial logistical challenges for the future efficacy of mCDR deployments and MRV efforts in regions of the ocean affected by others' actions months to years prior. The importance of models for MRV will grow as repeated real-life mCDR interventions move us further from the counterfactual scenario (i.e., a world with no mCDR interventions). Complex and potentially long-lasting effects of deploying diverse mCDR approaches demands globally linked modeling, observational, and deployment efforts to understand compounding interactions among them (Ombres et al., 2025).

To capture these globally linked mCDR efforts with rapid and complex biogeochemical responses at sites of deployment, models will need to represent linkages between field-scale and global processes. Simulations of near-field scale alkalinity and/or nutrient dynamics for mCDR deployments will require high performance computing infrastructure that can represent finer time steps at spatial resolutions of 100 m or less. These computational demands may also necessitate the use of GPU-capable software that can further exploit parallel processing schemes to achieve reasonable simulation times. Furthermore, integrating field-to-regional scale dynamics of mCDR activities within global processes will require some form of linkages between ocean dynamics that span 4–5 orders of magnitude spatially. This computational effort can only currently be accomplished with exascale computing systems, and may require further response curves to be implemented when transferring to larger scales (Zhou et al., 2024).

One important consideration regarding the use of modeling for MRV purposes is the energy needed to run simulations and the degree to which computing facilities run on renewable energy (Silva et al., 2024). For example, we estimate that simulating carbonate system dynamics in the Gulf of Alaska using ROMS-COBALT (Figure 3C) required about 24 h on ~224 cpu cores per simulated year. Refining the model to get these results required ~200 simulated years using roughly ~20,000 kWh of energy used just by the CPU (ignoring the contributions from cooling and data storage), which is ~2 times the average household energy consumption in the US (U.S. Energy Information, 2020). Global scale Earth system model simulations can use orders of magnitude greater computational resources depending on model complexity. As carbon removal strategies become increasingly reliant on sophisticated models for MRV, decarbonizing computational capabilities is one important consideration for ensuring that mCDR interventions result in net negative emissions. The need for repeatedly running new model simulations for either planning or verifying carbon removal of every individual mCDR deployment may also be alleviated as tools based on well-documented, repeated global simulations such as the OAE Efficiency Map emerge (Zhou et al., 2024). In this case, the "risk assessment for incomplete CO_2 equilibration" framework proposed by Bach et al. (2023) could be used to scale the value of carbon credits based on uncertainty in the simulations used for carbon removal verification, with more skillful model ensembles justifying higher value credits. Finally, Ho et al. (2023) suggests that training artificial intelligence and machine learning algorithms with well-calibrated model outputs, validated with actual field data, could be another viable approach for streamlining predictions of the carbon removal efficiency of future mCDR interventions.

While we primarily discussed how to adapt and improve modeling capabilities for the emerging field of mCDR, co-development of observing systems for MRV, detecting changes to the world's oceans, and validating new model developments is essential. As we improve and validate our models for mCDR and other new applications the community should explore what an ideal data-assimilative ocean model looks like, and how such a model can best support sampling efforts through approaches like Observing System Simulation Experiments, wherein model outputs can be repeatedly sampled to better determine optimal configurations for sampling strategies that inform forecasts (Hoffman and Robert, 2016). Likewise, when staging large scale field trials, models forecasting ocean conditions may have a better understanding of the likelihood of vertical mixing, flushing rates at time of deployment, and could immediately assess the carbon uptake efficiency *post hoc*. However, current state of the art predictive capabilities only support accurate forecasts up to a few days in advance when considering biogeochemistry (Bever et al., 2021). Accurate weather forecasting provided by aerial or future satellite platforms, as well as new artificial intelligence approaches for predicting weather, waves, and the ocean carbon system, may prove essential for such predictions (Rodríguez et al., 2018; Dong et al., 2022; Song et al., 2023; Roobaert, 2025).

Scientifically, we are still in the early days of assessing the efficacy and efficiency of diverse mCDR approaches. It is both likely and essential that public and private investment in decarbonization and carbon removal will grow exponentially in the coming decades necessitating strategic and concerted use of resources to create a sum greater than the whole of its parts. Doubling down on society's investment in ocean observing platforms via dedicated long term regional testing infrastructure (e.g., mCDR Centers of Excellence) that are distributed across diverse coastal and marine environments is one strategy for catalyzing transformational understanding of how humans can positively influence the Earth system and mitigate the deleterious effects we have had since the Industrial Revolution. Sustained observations of ocean carbon and biological systems (Boettcher et al., 2023) are critical for supporting continued development of the models we need to understand future Earth

system feedbacks as humans continue to intervene with natural processes both positively and negatively.

Author contributions

NW: Funding acquisition, Visualization, Writing – original draft, Writing – review & editing. KH: Funding acquisition, Visualization, Writing – original draft, Writing – review & editing. RP: Funding acquisition, Visualization, Writing – original draft, Writing – review & editing. JC: Writing – original draft, Writing – review & editing. MF: Funding acquisition, Writing – original draft, Writing – review & editing. CH: Funding acquisition, Writing – original draft, Writing – review & editing. PM: Funding acquisition, Writing – original draft, Writing – review & editing. CS: Funding acquisition, Writing – original draft, Writing – review & editing. JX: Visualization, Writing – original draft, Writing – review & editing. PS-L: Funding acquisition, Visualization, Writing – original draft, Writing – review & editing. ZY: Funding acquisition, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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