Science of the Total Environment 749 (2020) 141357

Contents lists available at ScienceDirect

Science of the Total Environment

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

The value of scientific research on the ocean's biological carbon pump

Di Jin [a,*], Porter Hoagland [a], Ken O. Buesseler [b]

[a] Marine Policy Center, Woods Hole Oceanographic Institution, Woods Hole, MA 02543, United States of America
[b] Marine Chemistry & Geochemistry Department, Woods Hole Oceanographic Institution, Woods Hole, MA 02543, United States of America

HIGHLIGHTS

- Ocean's biological carbon pump (BCP) constitutes one of Earth's most valuable ecosystem services.
- The value of marine scientific research on BCP carbon sequestration is investigated.
- The benefit to narrow the range of uncertainty about ocean carbon sequestration is on the order of $0.5 trillion.
- The value is affected by the accuracy of predictions, the economic parameters, and the initial range of uncertainty.

ARTICLE INFO

Article history:
Received 15 April 2020
Received in revised form 1 July 2020
Accepted 27 July 2020
Available online 1 August 2020

Editor: Martin Drews

Keywords:
Economic value of scientific research
Value of information
Biological carbon pump
Carbon sequestration
Ecosystem service
Ocean twilight zone

ABSTRACT

The ocean's biological carbon pump (BCP) sequesters carbon from the surface to the deep ocean and seabed, constituting one of Earth's most valuable ecosystem services. Significant uncertainty exists surrounding the amounts and rates of organic carbon sequestered in the oceans, however. With improved understanding of BCP sequestration, especially its scale, world policymakers would be positioned to make more informed decisions regarding the mitigation of carbon emissions. Here, an analytical model of the economic effects of global carbon emissions—including scientific uncertainty about BCP sequestration—was developed to estimate the value of marine scientific research concerning sequestration. The discounted net economic benefit of a putative 20-year scientific research program to narrow the range of uncertainty around the amount of carbon sequestered in the ocean is on the order of $0.5 trillion (USD), depending upon the accuracy of predictions, the convexities of climate damage and economic output functions, and the initial range of uncertainty.

1. Introduction

1.1. Policy context and relevance

In 2002, the World Summit on Sustainable Development (the Johannesburg "Earth Summit") established a "Regular Process" for reviewing the state of the world's oceans, including its socio-economic aspects. The Regular Process culminated in the publication, in 2016, of the *First Global Integrated Marine Assessment* (the World Ocean Assessment I or WOA1). Among its many findings, the WOA1 authors concluded that many of the natural structures and processes comprising the world's ocean systems had been seriously degraded by human activities, signifying that human uses of the ocean were following unsustainable paths (Inniss and Simcock, 2016). Further, it identified significant gaps in knowledge about ocean CO_2 absorption and nutrient cycling, among limits to understanding other important physical and geochemical processes.

In 2015, the UN General Assembly adopted its *2030 Agenda for Sustainable Development* (2030 Agenda) comprising 17 goals for sustainable development (SDGs), including those based on themes relating to energy, climate, the oceans, and science and technology, among many others. For each SDG, a set of target objectives were identified, and progress in achieving these targets was to be measured using one or more specified indicators. For SDG number 14 (SDG14), which is focused on the goal to "conserve and sustainably use the oceans, seas and marine resources for sustainable development," progress in assembling time series on indicators has been slow, but, for those indicators that can be represented by actual data, the relevant trends do not seem to be improving (UNSD, 2019). By implementing status reports and baselines about the oceans, the Regular Process was intended to motivate the attainment of the 2030 Agenda, especially the SDG14 targets and other ocean-relevant targets embodied in several other SDGs.

* Corresponding author.
E-mail addresses: djin@whoi.edu (D. Jin), phoagland@whoi.edu (P. Hoagland), kbuesseler@whoi.edu (K.O. Buesseler).

https://doi.org/10.1016/j.scitotenv.2020.141357

Importantly, the WOA1 report characterized the Earth's ocean and atmosphere as linked systems, necessitating the coordination of scientific research across both media in order to understand the full implications of climate change. More specifically, because of the important biophysical and geochemical linkages relating to carbon cycling, the WOA1 authors acknowledged the high degree of complementarity between the Regular Process assessments and the periodic reviews of global climate change undertaken by the Intergovernmental Panel on Climate Change (IPCC). A leading recent example of this complementarity comprised the 2019 *Special Report on the Ocean and Cryosphere in a Changing Climate* (SROCC), which assigned levels of confidence to observed and projected impacts and risks of climate change to a wide range of alterations in ocean states and dynamics.

One of the most critical—and valuable—ocean ecosystem services concerns the export of carbon from the surface ocean to the deep ocean and deep seabed. There are fundamental uncertainties about the processes of carbon export, including its driving mechanisms and fluxes, but a critical mechanism is known to involve the biological carbon pump (BCP). The biological pump entails several pathways by which particulate organic carbon (POC) is exported to the deep ocean (Boyd et al., 2019), including the sinking of phytoplankton—as individual cells or aggregates—as marine snow, the release of fecal pellets by zooplankton grazers, transport via mesopelagic diel migrating fish, and the seasonal migration and hibernation at depth of zooplankton in some regions. Scientists are still working out the mechanisms by which the biological pump operates, and they have been generating and testing hypotheses on the environmental factors that influence its operation (Henson et al., 2019; Boyd et al., 2019; Le Moigne, 2019; Siegel et al., 2016). Further, the extent to which ocean carbon export could be compromised by the climate-induced warming and increased stratification of surface waters, the widening of the oxygen minimum zone (OMZ), limits on nutrient fluxes, and acidification of sea water (Hofmann and Schellnhuber, 2009), have been suggested, but they are not known with any degree of confidence (IPCC, 2019). According to the SROCC authors:

> …different lines of evidence (including observation, modeling and experimental studies) provide low confidence on the mechanistic understanding of how climatic drivers affect different components of the biological pump in the epipelagic ocean, as well as changes in the efficiency and magnitude of carbon export in the deep ocean…this renders the projection of future contribution of the biological carbon pump to the export of POC to the deep ocean having low confidence.
>
> [(IPCC, 2019; p. 5–52)]

In 2017, recognizing that marine scientific observations and research were essential for measuring and predicting the responses of the oceans to climate change, the UN General Assembly proclaimed a *Decade of Ocean Science for Sustainable Development (2021–2030)* (the Decade). One of the central purposes of the Decade will be to ensure that ocean science can contribute to the sustainable development goals embodied in the 2030 Agenda, especially those relating to the ocean. Understanding the processes of carbon export, which now is believed to sequester between 20 and 30% of current levels of anthropogenic carbon emissions, is likely to emerge as one of the central research focuses of the Decade (Le Quéré et al., 2018; Lindoso, 2019). The knowledge and insights resulting from the Decade's research are envisioned to provide support for decisions to conserve and manage human uses of the ocean so that both current and future generations can continue to benefit from its extraordinary array of ecosystem services, including its highly valuable regulating services.

The Intergovernmental Oceanographic Commission (IOC) of UNESCO has been chosen to coordinate the efforts of the international community in sponsoring and undertaking the relevant science, but an absence of national interest backed by funding now threatens to limit the extent to which the Decade can realize its potential (cf., Isensee et al., 2017). To date, the scale in economic terms of the benefits provided by the oceans in sequestering anthropogenic carbon emissions—and the risks imposed by climate change to the maintenance of those benefits—have not been fully evaluated and recognized. The methods and estimates presented here are an important first step at elucidating those benefits and, more specifically, in formulating a strong economic argument for carrying out the research program envisioned by the Decade. Without such an argument, the goals for sustainable development of the oceans, as articulated in the 2030 Agenda, are unlikely to be realized, the health of the Earth's oceans will continue to wane, and the capacity of the oceans to mitigate damages from climate change may be irrevocably compromised.

In terms of scale and economic significance, the restructuring of the global carbon cycle and the accompanying alteration of the climate comprises the largest transformation of natural systems ever experienced in modern times. All humans who have ever lived have abetted this change, but human activities from the industrial revolution forward have made the weightiest contributions (Hsiang and Kopp, 2018). During 2008–2017, global anthropogenic carbon emissions increased every decade from an average of 3.1 Gt C/yr in the 1960s to an average of 9.4 Gt C/yr today (Le Quéré et al., 2018).

The purpose of this study was to scale the potential value of information that could be provided by marine scientific research about carbon sequestration in the ocean. The value of information is defined as a difference in the economic consequences of adopting a policy action, with-and-without the knowledge and understanding provided through investments in scientific research. Investments in scientific research could improve human understanding of the workings of natural systems, enhancing abilities to predict future states of nature. Science-based understanding could lead to a more reasoned consideration and choice of policies and management actions, which in turn could lead to improvements in human welfare. Moreover, in the specific case examined here, assessments of the value of research for reducing uncertainty regarding ocean carbon sequestration could be used to help inform the appropriate scale of public investments in the science itself.

An analytical framework for assessing the value of marine scientific research in the presence of uncertainty about BCP sequestration was developed.[1] The value of research to reduce this uncertainty was measured in terms of potential increases in global welfare associated with more accurate carbon emission controls. Alternatively, should better scientific knowledge on BCP sequestration become available but nevertheless be ignored by policy makers, this value could be considered an estimate of the potential cost of ignoring the relevant scientific information.

The earth's natural systems are complex, and the coupled natural and human systems are even more so. To improve our understanding of the many mechanisms and feedback interactions will require extensive scientific research efforts and the consequent accumulation of knowledge over time. In this study, we assess the value of a specific form of research (BCP sequestration), assuming that the research will reduce relevant uncertainties from previous work.

1.2. Literature review

Apart from the atmosphere, there are two major natural sinks of carbon, terrestrial and oceanic. The global ocean has absorbed roughly one-third of the anthropogenic CO_2 emitted during the industrial period

[1] A substantial amount of work on ocean organic carbon sequestration has been done since the seminal work of Martin et al. (1987). Among others, key papers (e.g., Armstrong et al., 2001; Boyd et al., 2019; Buesseler et al., 2007; Klaas and Archer, 2002; Marsay et al., 2015) present examples on how research on the BCP evolved during the past three decades. These studies all point to different mechanisms influencing the strength of the ocean's biological carbon pump, often complicating the initial picture provided by Martin et al.

(Khatiwala et al., 2013).[2] Carbon is sequestered in the oceans through two mechanisms: a solubility pump, which comprises a physico-chemical process that slowly transports carbon, as dissolved inorganic carbon, from the ocean's surface to its interior, and a biological carbon pump (BCP), which comprises a more rapid biologically driven sequestration of carbon from the atmosphere to the ocean interior and seafloor sediments.

The stocks and flows of carbon in the ocean have been identified and described in broad terms, but considerable uncertainty still remains about the mechanics of the ocean carbon cycle, especially in the face of shifting ambient environmental conditions. Climate change is expected to lead to a more stable stratification of ocean waters and a general slowing down of large-scale mixing and circulation, causing a lowered uptake of anthropogenic carbon and reductions in the supply of nutrients to help drive the BCP (IPCC, 2019). Using biogeochemical models, Barange et al. (2017) estimated the costs associated with potential reductions in carbon sequestration by the BCP in the North Atlantic Ocean over the 21st century. These authors estimated that carbon flux at 1000 m in the North Atlantic would decline 27–43% by the end of the century.[3] Over the 90 yr study period, the costs to offset this lost service through the abatement of carbon emissions would require between \$0.2–3.0 trillion (USD).

The literature has begun to address the value of scientific research in the context of environmental and marine resource management (Lave, 1963; Adams et al., 1995; Bernknopf et al., 1997; Schimmelpfennig and Norton, 2003; Costello et al., 2010). Further, several studies have assessed the value of information in climate research and emission control policy. Peck and Teisberg (1993) estimated the value of information about global warming uncertainties in a simple decision-tree framework by investigating the sensitivity of optimal carbon control strategies to changes in parameters of the Carbon Emissions Trajectory Assessment (CETA) Model. These authors found that, if a policy of optimal emission controls under uncertainty was implemented, the resolution of uncertainty had a high value relative to scientific research budgets, and resolving uncertainty about the costs of warming was nearly as important as resolving uncertainty about the extent of warming.

Cooke et al. (2014, 2017) developed estimates of the value of information for climate observing systems (i.e., the proposed space borne CLARREO [Climate Absolute Radiance and Refractivity Observatory]). In their analyses, when the rate of temperature rise exceeded a critical value with sufficient confidence, the optimal policy response was to switch from a business-as-usual emissions path to a reduced emissions path. Uncertainty about observed global average temperature is a result of both natural variability and instrument measurement errors. With the CLARREO technology in place, measurement errors would be reduced, leading to a higher level of confidence about temperature increases and allowing society to reduce emissions sooner, thereby avoiding damages that otherwise would be incurred by business-as-usual emissions. Climate damages and abatement costs were estimated using the DICE (Dynamic Integrated Climate-Economy) model developed by Nordhaus (1993, 2017). Under discount rates of 2.5%, 3% and 5% the “option value” of CLARREO was \$16.7, \$9.0 and \$1.1 trillion (2008 USD), respectively.[4]

Hope (2015) used the PAGE09 (Policy Analysis of the Greenhouse Effect 2009) model to estimate the value of better information about “transient” climate response, the increase in global mean temperature resulting from a doubling of the concentration of CO_2 in the atmosphere in 70 years. In that study, the preferred policy response was to optimize the carbon emissions path to minimize both climate change impacts and abatement costs. New information would reduce the range of uncertainty about the transient response. The probabilistic structure of the model enabled the author to simulate climate damage (with adaptation) and abatement costs for different uncertainty ranges. Simulation results showed that a 50% reduction in the uncertainty range for a transient climate response had a net present value of about \$10.3 trillion (2005 USD) if accomplished in time for emissions to be adjusted by 2020, falling to \$9.7 trillion if accomplished in time for emissions to be adjusted by 2030.

Freeman et al. (2015) provided a different and supplementary justification for a vigorous climate science research effort. These authors considered what the value of advancements in climate science would be if policy makers could not respond to new information about climate change because international climate agreements were ineffective. The authors argued that better predictions about the consequences of climate change would lead to better adaptation through consumption smoothing (precautionary savings in anticipation of future losses) and protective measures (e.g., flood defenses or choice of location) to reduce damages.

Pindyck (2012) estimated the fraction of consumption that society would be willing to sacrifice to ensure that any increase in temperature at a future point was generally below 2%, even for small values of temperature increase, which was consistent with moderate abatement policies. He also calculated willingness to pay (WTP) for shifts in the mean and standard deviation of the temperature distribution. His results showed that uncertainty over temperature change could be a stronger driver of WTP than expectations, and thus should be a major focus of climate change policy.

2. Biological carbon pump

Carbon sequestration is defined as the long-term or near-permanent storage of carbon in a given area. The oceans provide a crucial ecosystem service by sequestering carbon through the BCP (Boyd et al., 2019; Barange et al., 2017). The vertical transport of carbon and its sequestration via the BCP strongly affects the atmospheric levels of CO_2 (Kwon et al., 2009), making it essential to understand the carbon flux mechanisms of the BCP.

The euphotic zone is the sun-lit surface layer of the ocean, where primary production takes place as phytoplankton use atmospheric CO_2 in its dissolved inorganic carbon (DIC) form and sunlight to form particulate organic carbon (POC) and particulate inorganic carbon (PIC). The sequestration of carbon is mainly carried out via gravitational sinking of particles from the euphotic zone to the deep ocean (Antia et al., 2001; Buesseler et al., 2007). As recently reviewed by Boyd et al. (2019), several other “pumps” can contribute to carbon sequestration. These include carbon transport via mesopelagic diel migrators (Bianchi et al., 2013) and, in some regions, the seasonal migration and hibernation of zooplankton at greater depths during winter months (Jónasdóttir et al., 2015). In addition, there are several physical pumps that inject surface waters and suspended and dissolved organic matter to depth (Levy et al., 2013; Stukel et al., 2018). Of these non-gravitational pumps, the seasonal migration and diel migration (assuming production of efficiently sinking particles at depth), can approach levels of carbon sequestration equivalent to gravitational settling, when considering carbon transport and sequestration below 1000 m. While on average 10% of the carbon leaving the euphotic zone reaches 1000 m, only about 1% of the carbon produced in the euphotic zone is thought to reach the ocean floor where it can remain for even longer

[2] Khatiwala et al. (2013) estimated that, by 2010, the global ocean inventory of anthropogenic carbon was 155 ± 31 Gt C.

[3] At a depth of 1000 m, it is assumed typically that carbon has been sequestered for centuries or longer. Results of an analysis using a global ocean general circulation model suggest that the time scale it takes for deep water to reach the surface varies by location, ranging from 100 to more than 1000 years (Primeau, 2005).

[4] In 2017, Cooke et al. published an enhanced version of their earlier (2014) value of information calculation. In the enhanced study, the value of a new observing system was calculated as the value associated with the “option” to use the new system in making optimal future climate policy choices, rather than using the existing system. Because emission control policies were examined over a century-long time period (2015–2115), the results were sensitive with respect to the discount rate.

time scales than deep ocean ventilation time scales (millennia) (Sanders et al., 2014).

Ultimately, the degree of primary production and its attenuation with depth determine the strength and efficiency of the BCP (Barange et al., 2017), with export production (EP) commonly used to define the carbon flux at a particular depth. Thus, the efficiency of carbon sequestration is determined by the magnitude of EP and processes that attenuate flux, which include both physical breakdown and biological consumption, the impact of which will also depend on changes in particle sinking velocity (Taucher et al., 2014; Villa-Alfageme et al., 2016). Both POC production and the strength of the BCP are expected to decline in response to lowered nutrient supply with warming and increasing sea surface temperatures (Matsumoto et al., 2010; Manizza et al., 2010). Changes to the algal and zooplankton community structures in the subsurface ocean are expected to have the greatest influence on POC flux (Boyd, 2015), but these are difficult to predict. A weakened BCP would lead to reduced ocean carbon storage, exacerbating atmospheric CO_2 levels, and causing atmospheric temperatures to rise.

There are many uncertainties in the quantification of EP in the global ocean due to spatiotemporal variations and an incomplete understanding of the potential effects of climate change on the biogeochemical processes involved in carbon sequestration (Boyd and Trull, 2007). Current global annual estimates of EP from the surface ocean from multiple independent studies range from 5 PgC (or GtC) to more than 12 PgC per year (Boyd and Trull, 2007; Henson et al., 2011; Siegel et al., 2016). This enormous uncertainty reflects a poor understanding of the BCP, due to its natural variability and limited observations of the magnitude of EP and processes controlling the BCP efficiencies. The premise of the assessment presented here is that additional research will improve our understanding and reduce these uncertainties (Siegel et al., 2016).

3. Analytical framework

Climate policy research utilizes integrated assessment models (IAMs), which integrate socioeconomic scenarios that produce future emissions trajectories. The trajectories are fed into a climate model that translates emissions paths into carbon concentrations, producing scenarios for future temperatures, precipitation, sea levels, and other environmental conditions. These climatic outcomes are then fed into a set of damage functions, which map the climate model output into economic damages at the global or regional level (Auffhammer, 2018). DICE and PAGE are two well-known IAMs.

Policies concerning the levels of global carbon emissions are investigated here using the DICE framework (Nordhaus, 1993, 2017). To avoid unnecessary complexity and to focus on the value of marine scientific research, the DICE model, as outlined in the Appendix 1, has been streamlined; in particular, a multi-period environment is not modeled formally. Key interactions affecting the value of marine scientific research on the BCP are thereby highlighted, ignoring many complex, dynamic effects, such as population growth, technological change, and discounting.

Define social welfare (W) in a year as follows:

$$W[C(q)] = U\{Y(q) - D[N(q) + N_0]\} \tag{1}$$

where C is consumption; Y is gross economic output less investment; D is climate damage; N is the growth in carbon concentration in the atmosphere; N_0 is the stock of carbon in the atmosphere at the beginning of the year, and q is the carbon emission target.[5] Because both Y and D are functions of q, and $C = Y - D$, consumption is regulated by the emission target.

The damage function is a mapping of climate conditions (i.e., carbon concentration) into economic outcomes, which include negative economic effects on various economic sectors (e.g., crop damages in agriculture, changes in energy production and consumption, and disease outbreaks affecting public health (Le Quéré et al., 2020)), storm damages, coastal hazards resulting from sea-level rise, and other social, environmental, and ecological impacts. The damage function also accounts for adaptation[6] and abatement[7] costs.

Because climate change is a global phenomenon, it can be challenging to quantify economic damages, which vary across space and time. In addition, the effects of greenhouse gas emissions at one point in time can persist for hundreds of years. Unit damage is expected to increase over time, because of the rising stock of greenhouse gases in the atmosphere and the vulnerability associated with economic growth (Nordhaus, 2017; Auffhammer, 2018). In addition, climate change may affect carbon export in the ocean (Laws et al., 2000; Bopp et al., 2001; Manizza et al., 2010; Barange et al., 2017).

The social welfare, economic production, and climate damage functions have the following properties:

$$\frac{\partial W}{\partial C} \geq 0, \frac{\partial^2 W}{\partial C^2} \leq 0, \frac{\partial Y}{\partial q} \geq 0, \frac{\partial^2 Y}{\partial q^2} \leq 0, \frac{\partial D}{\partial N} \geq 0, \frac{\partial^2 D}{\partial N^2} \geq 0. \tag{2}$$

Greater benefits are associated with higher levels of consumption (C) which require greater output (Y) and lower climate costs (D). Both Y and D are positively related to the level of carbon emissions (q).

The growth in carbon concentration in the atmosphere in a year (N) equals the carbon emissions (q) less carbon sequestered on land (L) and in the oceans ($M_L + z\rho$)[8]:

$$N(q) = q - L - M_L - z\rho \tag{3}$$

To bound the uncertainty about BCP sequestration, z is the difference between high- and low-end estimates of annually sequestered organic carbon[9]:

$$z = M_H - M_L > 0 \tag{4}$$

Uncertainty is modeled by the stochastic variable ρ with $0 \leq \rho \leq 1$. In Eq. (3), $z\rho$ is the actual amount of carbon sequestered by the BCP above M_L. There are two corner cases. In the first, $\rho = 0$ and the ocean sequestration is M_L. In the second, $\rho = 1$, and the ocean sequestration is M_H. One primary objective of a program of marine scientific research is to estimate out how much carbon is sequestered by the oceans. Without prior information about ρ, assume that ρ follows a probability density function $\varphi(\rho)$. The expected value of BCP sequestration is $M_L + zE(\rho)$. Note that N is the change in atmospheric carbon in a year, given the stock of atmospheric carbon at the beginning of the year. N can be negative when carbon emissions are smaller than the sum of sequestration on land and in the ocean.

3.1. Socially optimal carbon emission level under uncertainty

Given the effect of stochastic variable ρ (and in turn N) on W, the problem is to identify the optimal level of emission (q) so that the expected social welfare (W) is maximized, or, maximizing the expected

[5] The emission target could be implemented through a global action plan. For example, the plan under the Paris Agreement of 2015 was to limit global warming 'well below' 2 °C.

[6] Climate change adaptation is a response to global warming that seeks to reduce the vulnerability of social and biological systems to relatively sudden change and thus offset the effects of global warming.

[7] The cost of reducing greenhouse gas emissions.

[8] On the global carbon budget, Le Quéré et al. (2018) estimated that in the decade from 2008 to 2017, fossil CO_2 emissions were 9.4±0.5 GtC/yr, land-use change (mainly deforestation) 1.5±0.7 GtC/yr, the growth rate of atmospheric CO_2 concentration 4.7±0.02 GtC/yr, the ocean CO_2 sink 2.4±0.5 GtC/yr, and the terrestrial CO_2 sink 3.2±0.8 GtC/yr, with a budget imbalance of 0.5 GtC/yr (all uncertainties are reported as ±1 standard deviation), indicating overestimated emissions or underestimated sinks due to imperfect data and understanding of the contemporary carbon cycle. Here we focus only on the uncertainty associated with the BCP.

[9] This formulation does not explicitly consider uncertainties associated with other ocean carbon sequestration mechanisms (e.g., the solubility pump).

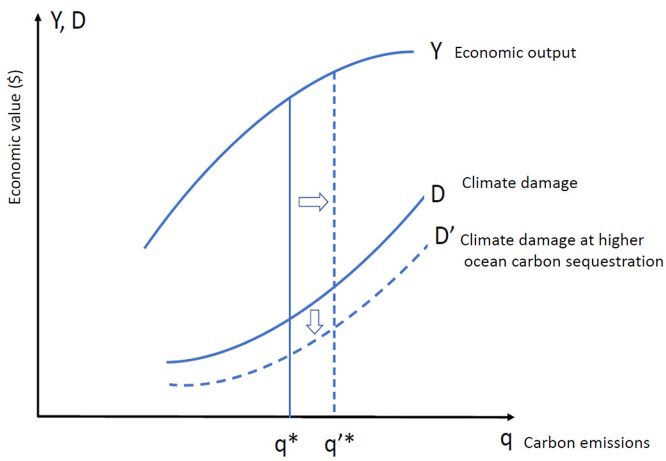

Fig. 1. Optimal carbon emission target q*. An increase in BCP sequestration leads to a reduction in climate damages (a downward shift of D to D') at a new higher level of economic output (a right shift to q'^{*}), and vice versa.

value of objective function (1) subject to constraint (3). Focusing on an optimal carbon emission level, consider q to be a control variable. From Eq. (1), choose q to maximize:

$$max\ E\{W[C(q)]\} = U\{Y(q) - E\{D[N(q) + N_0]\}\} \tag{5}$$

The first order condition is:

$$\frac{dY}{dq} = \frac{dE(D)}{dN}\frac{dN}{dq} \tag{6}$$

The left-hand-side of Eq. (6) is the marginal benefit of carbon emissions in terms of increased economic output, and the right-hand-side is the expected marginal damage. The solution to Eq. (6), q^*, is the optimal level of carbon emissions, assuming certainty about outputs. As illustrated in Fig. 1, at q^* the net benefit of carbon emissions (the vertical distance between the benefits of increased economic growth, Y, and the costs of carbon emissions, D) is maximized. An increase in BCP sequestration would lead to a reduction in climate-associated damages (a downward shift of D to D') and a new higher level of economic output (a right shift to q'^{*}), and vice versa. Within this framework, it is important to recognize that a benefit of increased BCP sequestration comprises growth in economic output, which itself implies higher levels of carbon emissions.

Specify the output function to be:

$$Y(q) = \theta + \omega q^{\gamma} \tag{7}$$

where θ, ω, and γ are coefficients. Output is concave with respect to q and $0 < \gamma < 1$.

The damage caused to the economy and environment (D) is a function of accumulation of atmospheric carbon:

$$D(N + N_0) = \begin{cases} \eta N^{\lambda} + D_0(N_0) & N > 0 \\ D_0(N_0) & N \le 0 \end{cases} \tag{8}$$

where $\eta > 0$ is a coefficient, $\lambda \ge 1$ is a coefficient to capture the nonlinear effect of N on climate damage. D_0 is the annual damage associated with N_0 (the stock of carbon in the atmosphere).[10]

[10] When $N \le 0$, the stock of carbon in the atmosphere is not increasing or decreasing in that year. Here, we assume no incremental damage beyond the base damage associated with N_0 and ignore a possible net reduction in total damage. Note that the incremental damage associated with a positive increase in N is always greater than the reduction in damage resulting from a negative N, because climate damage function is convex (see Figure 1).

Substituting Eq. (3) into Eq. (8), and noting that ρ is stochastic:

$$\begin{aligned} E\{D[N(q) + N_0]\} &= \int_0^1 \left(\eta N^{\lambda}\right)\varphi(\rho)d\rho + D_0(N_0) \\ &= \int_0^1 \eta(q - L - M_L - z\rho)^{\lambda}\varphi(\rho)d\rho + D_0(N_0). \end{aligned} \tag{9}$$

Substituting Eqs. (7) and (9) into Eq. (6) yields:

$$\omega\gamma q^{\gamma-1} = \eta\lambda \int_0^1 (q - L - M_L - z\rho)^{\lambda-1}\varphi(\rho)d\rho. \tag{10}$$

For $\lambda = 2$ and $\gamma = 1$, the optimal level of emission can be solved using Eq. (10):

$$q^* = \frac{\omega}{2\eta} + L + M_L + zE(\rho) \tag{11}$$

For a specific set of parameters, q^* increases as the mean of ρ becomes larger. Thus, the results suggest that when more carbon is absorbed by the BCP, the optimal level of carbon emissions (q^*) can be set higher than that associated with a lower ρ. This result highlights the importance of marine scientific research on BCP to climate policy.

The resulting expected social welfare Eq. (5) is:

$$W^* = E[W(q^*)]. \tag{12}$$

3.2. Value of information

A standard Bayesian approach can be used to estimate the value of information resulting from scientific research (Kite-Powell and Solow, 1994; Adams et al., 1995; Jin et al., 2006; Jin and Hoagland, 2008). Society would choose a carbon emission level (q), and the resulting social welfare (W) would depend upon the state of nature (ρ), which is unknown at the time of the choice. The prior probability density function (pdf), $\varphi(\rho)$, reflects society's existing knowledge about ρ. Note that $0 \le \rho \le 1$.

Suppose that research is conducted to develop a prediction of ρ. Let s represent the prediction. According to Bayes' theorem, the posterior pdf of ρ, given s:

$$\varphi(\rho|s) = \frac{l(s|\rho)\varphi(\rho)}{g(s)} \tag{13}$$

where $l(s|\rho)$ is the likelihood that prediction s will have been made, given the true value of ρ, and

$$g(s) = \int l(s|p)\varphi(\rho)d\rho \tag{14}$$

is the pdf of s. The posterior pdf of ρ summarizes all the information by combining the prior information and additional information from scientific research (s). Essentially, the prior $\varphi(\rho)$ represents current understanding of ρ without research, and the posterior $\varphi(\rho|s)$ reflects an improved understanding of ρ with research.

With each prediction (s), society uses the posterior distribution to find a new optimal emission level by choosing q to maximize:

$$max\ E[W(q|s)] = U\{Y(q) - E\{D[N(q|s) + N_0]\}\} \tag{15}$$

with $Y(q)$ defined as in Eq. (7) and

$$E\{D[N(q|s) + N_0]\} = \int_0^1 \left[\eta(q - L - M_L - z\rho)^{\lambda}\right]\varphi(\rho|s)d\rho + D_0(N_0) \tag{16}$$

For $\lambda = 2$ and $\gamma = 1$, the optimal emission level with prediction s, q_s^*, is the same as Eq. (11) except that $E(\rho)$ is replaced with the conditional mean

$$E(\rho|s) = \int_0^1 \rho\varphi(\rho|s)d\rho. \tag{17}$$

The resulting expected net benefit $E[W(q_s^*)]$ (see Eq. (15)) is conditional on the prediction of s, because the optimal activity level q_s^* is now affected by s and the range of prediction (s) is $0 \le s \le 1$. The expected social welfare with scientific research is:

$$W_s^* = \int_0^1 E\left[W\left(q_s^*\right)\right]g(s)ds \tag{18}$$

The expected net benefit W^* in Eq. (12) is measured without a prediction (s). Thus, the value of marine scientific research is:

$$\Delta W = W_s^* - W^* \tag{19}$$

Because the precision of prediction (s) may be improved through scientific research, Eq. (19) may be used to determine *ex ante* the level of improvement that must be achieved to justify a given level of investment in research.

This framework also can be used to estimate the value of perfect information associated with the limiting case in which environmental research is conducted to resolve all of the uncertainty. For that case, a perfect prediction comprises: $l(s|\rho) = 1$, if $s = \rho$, and 0 otherwise.[11] For each specific prediction, the true ρ would be known with certainty and society would choose the optimal activity level (q_s^*) for the true ρ. The expected net benefit with perfect information would be calculated using the prior $\varphi(\rho)$, instead of $g(s)$, in Eq. (18). The *ex ante* value of perfect information then is the average increase in the net benefit that results from optimizing the emission level under the certain knowledge of ρ rather than under the prior distribution.[12]

4. Simulation and results

Numerical simulations are developed using the analytical model described in the previous section. To facilitate the simulations, consider a Beta distribution[13]:

$$\varphi(\rho) = \frac{\rho^{\alpha-1}(1-\rho)^{\beta-1}}{B(\alpha\beta)} \tag{20}$$

where $0 \le \rho \le 1$, $\alpha > 0$ and $\beta > 0$ are parameters, and $B(\alpha, \beta)$ is the Beta function ($= \Gamma(\alpha)\Gamma(\beta)/\Gamma(\alpha + \beta)$). Note that when $\alpha = \beta = 1$, $\varphi(\rho)$ becomes a uniform distribution, representing a case in which society does not have any knowledge of ρ.

For the prior,

$$E(\rho) = \frac{\alpha}{\alpha+\beta}. \tag{21}$$

Specify a Beta likelihood pdf:

$$l(s|\rho) = \frac{s^{a-1}(1-s)^{b-1}}{B(a,b)} \tag{22}$$

with

$$E(s|\rho) = \frac{a}{(a+b)} = \rho \tag{23}$$

where $0 \le s \le 1$, $a > 0$ and $b > 0$ are parameters, and $B(a, b)$ is the Beta function. The likelihood function is a measure of the accuracy of the prediction. Assume that marine scientific research leads to correct predictions on average (i.e., the conditional mean of s equals ρ). From Eq. (23),

$$b = a\left(\frac{1}{\rho} - 1\right) \tag{24}$$

The variance of prediction is:

$$Var(s|\rho) = \frac{ab}{(a+b)^2(a+b+1)} \tag{25}$$

In the above specification, the accuracy of prediction (i.e., the variance) can be modeled by changing the parameter a.

Table 1
Parameters for simulations.

Parameter	Description	Value	Unit
M_L	C sequestered in ocean low estimate	2.3	10^{15}gC/y
M_H	C sequestered in ocean high estimate	5.5	10^{15}gC/y
L	C sequestered on land	3	10^{15}gC/y
ω	Output coefficient	8000	$\$10^9/(10^{12}\text{gC})^\gamma$/y
θ	Output coefficient	60,000	$\$10^9$/y
γ	Output coefficient	0.3, 0.4, 0.5	Dimensionless
η	Damage coefficient	2000	$\$10^9/(10^{12}\text{gC})^\lambda$/y
λ	Damage coefficient	1.8, 2.0, 2.2	Dimensionless

Parameter values for the simulation are summarized in Table 1. As shown in the table, POC flux estimates evaluated at a depth of 500 m range from 2.3 to 5.5 PgC/year,[14] comprising bounds on low- and high-end values for carbon sequestration in this study (Buesseler et al., 2007). For our purposes, this is a reasonable depth to consider for C sequestration, as carbon needs to be transported below several hundred meters in the ocean to be sequestered on average longer than the time scales of annual mixing and where it is isolated from contact with the atmosphere for hundreds of years or more (Primeau, 2005; Palevsky and Doney, 2018). Further, 3 PgC/year is assumed to be the level of terrestrial carbon sequestration (Le Quéré et al., 2018). Coefficients for the output function and climate damage function were selected to approximate DICE model scenarios between 2015 and 2020.

Consider first the relationship between research and the level of uncertainty about ρ by looking at the interactions among prior, likelihood, and posterior distributions. Four scenarios represented by different priors have been plotted in Fig. 2: (a) a uniform distribution ($0 \le \rho \le 1$) representing a scenario in which these is no prior knowledge about ρ; (b) a Beta distribution suggesting ρ is relatively small; (c) a distribution suggesting ρ is relatively large; and (d) an intermediate case.[15] In all cases, research leads to a reduction in the level of uncertainty (i.e., the variance of the posterior). The posterior combines the information in the likelihood with the prior information. For example, the peak of posterior in (b) is to the left of that in (c), a feature from the priors.

Next, optimal emission levels both with and without research were calculated for a nonlinear damage function, taking $\lambda = 2$. Without research, the uncertainty about the value of ρ is reflected in the prior, and the optimal emission (q^*) is affected by $E(\rho)$ (see Eq. (11)). For a uniformly distributed prior, $q^* = 6.58$ GtC/year. If the level of uncertainty is reduced through research, however, the emission target (q_s^*) can be estimated based on information embodied in the posterior. Of

[11] Here we consider the Bayes' theorem in a discrete form.
[12] This is consistent with the framework to estimate the expected value of perfect information (EVPI) developed by Peck and Teisberg (1993).
[13] The beta distribution is versatile because it has two parameters which can be chosen to reflect any existing belief or information without loss of generality (Bickel and Doksum, 2001).
[14] 1 PgC (10^{15}gC) = 1 GtC (10^9tC).
[15] Note that in each case, the likelihood and posterior pdfs are bivariate ($0 \le \rho \le 1$ and $0 \le s \le 1$). We show only $l(s|\rho$=0.5) and $\varphi(\rho|s = 0.5)$.

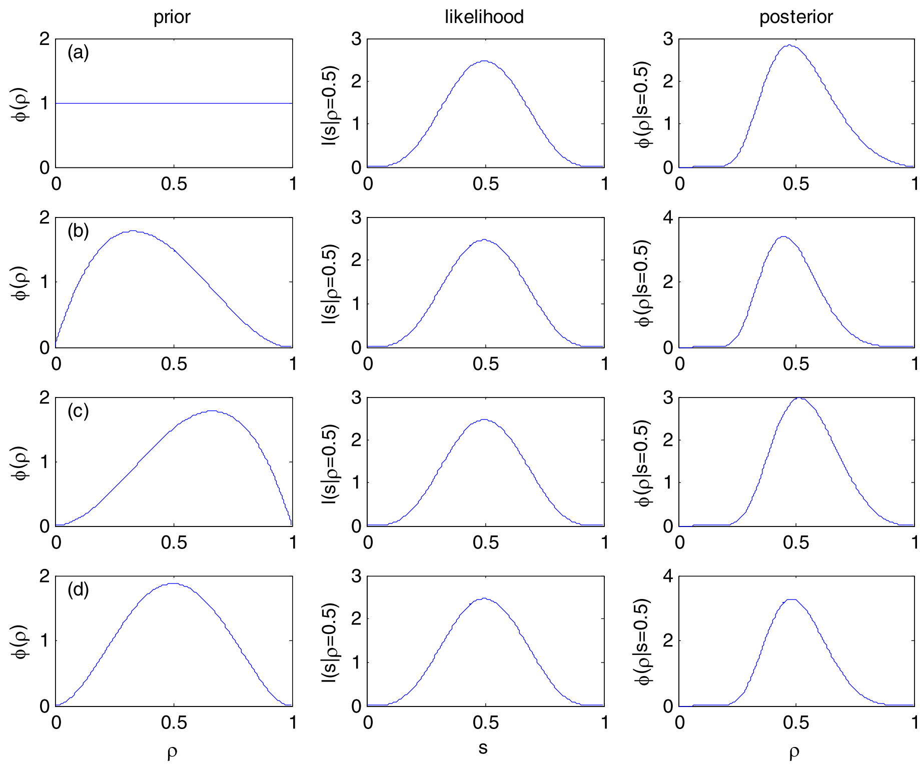

Fig. 2. Prior, likelihood, and posterior distributions ($a = 5$). Parameters for the prior (beta) distribution: (a) $\alpha = \beta = 1$; (b) $\alpha = 2, \beta = 3$; (c) $\alpha = 3, \beta = 2$; and (d) $\alpha = 3, \beta = 3$.

course, the value of q_s^* depends upon the prediction (s) of ρ. When $s \approx 0$, BCP sequestration is expected to be close to the low-end estimation (M_L). As a result, q_s^* is lower than q^*. In contrast, when s is high, and BCP sequestration is closer to the high-end estimation (M_H), q_s^* is higher than q^*. Fig. 3 plots carbon emission levels (q_s^*) over the range of predictions. As shown in the figure, under a uniformly distributed prior, the carbon emission target would range from 5.59 GtC/year to 8.63 GtC/year.

A difference between q_s^* and q^* leads to a difference in net social benefits (ΔW, see Eq. (19)), which comprises the *ex ante* value to society of sponsoring research to resolve uncertainty about ρ. In Fig. 4, the values by the level of the accuracy of prediction are depicted for all four priors ((a) through (d)).[16] Although the value of information rises as the accuracy improves, the growth rate declines with respect to the level of precision. This implies a diminishing return with respect to investment in research. This is because the initial range of uncertainty and the adjustment in emission target (from q^* to q_s^*) are larger than those of the subsequent ones. In addition, the value of information is largest when there is no knowledge about ρ (scenario (a)) and smallest when prior knowledge indicates that ρ is near the mid-point between M_L and M_H. When the prior suggests that ρ is relatively large, a further reduction in uncertainty through research would lead to greater economic benefits. Thus, the value of information associated with scenario (c) is also fairly large.

The value of information is affected by the difference between the optimal emission targets with prediction and without it (q_s^* and q^*), and these targets are influenced by the coefficients of the benefit function (γ in Eq. (7)) and the damage function (λ in Eq. (8)). In addition, the value is influenced by the range of uncertainty (z in Eq. (10)) in ocean carbon sequestration (e.g., the high-end estimate of BCP sequestration M_H).

As noted, the parameters used in the simulations were derived from the literature reflecting our current understanding the climate, ocean and economic systems (Buesseler et al., 2007; Nordhaus, 2017), constituting a set of fairly realistic scenarios. For example, $\lambda = 2$ follows the

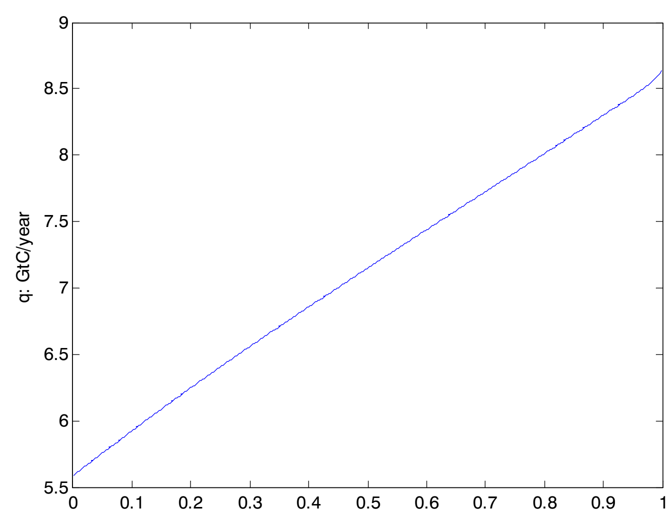

Fig. 3. Emission target by prediction. The prior is uniformly distributed ($\alpha = \beta = 1$); $a = 20$ in the likelihood function; and q represents emission target.

same specification in the DICE model, which is based on the observation that damages are a quadratic function of temperature change resulting from carbon emissions (Nordhaus and Sztorc, 2013). In our sensitivity analysis, we examine the range of 1.8–2.2 for λ to see how research value estimation varies by the damage function parameter. Similarly, we run simulations for γ from 0.3 to 0.5 for M_H from 3.3 to 7.0 PgC/y.

Figs. 5 and 6 summarize the results of sensitivity analysis with respect to these parameters, finding that the value of research is positively related to λ, γ, and M_H, which control the curvatures (marginal changes) of the climate damage function, the economic output function (see Fig. 1), and the range of uncertainty (z). Greater marginal changes suggest that either the cost or the benefit function is more sensitive to changes in emissions (q), which is determined by the prediction (s).

[16] This is implemented by changing the parameter value of a from 5 to 20 (the coefficient of variation ranges from 0.29 to 0.15).

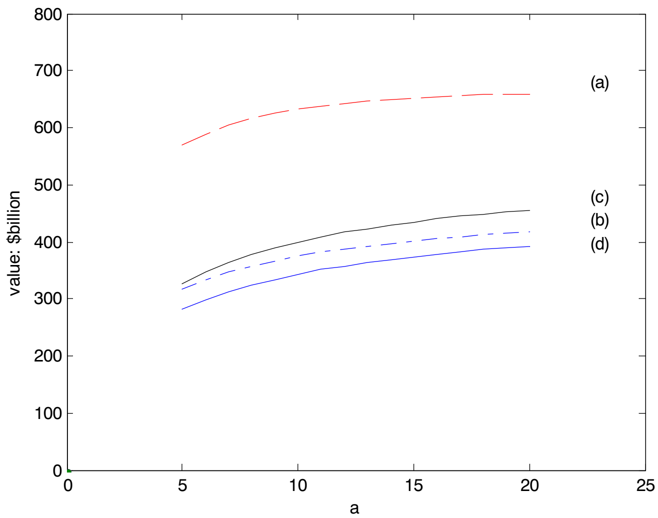

Fig. 4. *Ex ante* value of information. Parameter a in the horizontal axis represents the level of the accuracy of prediction. The plot depicts the value of research for all four priors shown in Fig. 2: (a) $\alpha = \beta = 1$; (b) $\alpha = 2, \beta = 3$; (c) $\alpha = 3, \beta = 2$; (d) $\alpha = 3, \beta = 3$; and ΔW is measured in billions of dollars.

For the set of parameters specified in the simulations, the value of research is more sensitive to parameter changes in the benefit function (γ) than in the cost function (λ), and it is most sensitive to the range of uncertainty (M_H). As the high-end estimate of BCP sequestration (M_H) rises from 3.3 to 7.0 PgC/y, the value of research increases from $0.1 to $1.1 trillion (Fig. 5). This result is not surprising, because the purpose of research is to reduce uncertainty about ocean carbon sequestration. As expected, the emission target q_s^* is negatively related to λ and positively related to γ and M_H (Fig. 6).[17] Again, the emission target is least sensitive with respect to λ and most sensitive with respect to M_H. As the high-end estimate of BCP sequestration (MH) grows from 3.3 to 7.0 PgC/y, the emission target rises from 6.0 to 6.8 GtC/y.

There is a diminishing return in the value of research with respect to continuous investments to improve the precision of prediction (Fig. 4). In a long-term research program to reduce the uncertainty about BCP sequestration, initial payoffs from research efforts are typically the highest, as the range of uncertainty narrows, subsequent gains decline, as the management policy (i.e., the emission target) is nearly optimal. As an illustration, we consider a hypothetical 20-year research program. The incremental value in each year resulting from improved prediction precision (parameter a) can be viewed as a flow of benefits, and we calculate the net present values (NPVs) of the total value of the program as in a cash-flow analysis using a discount rate of 3%.[18]

Using the baseline parameters in Table 1, the calculations are summarized in Table 2. As before, scenarios (a) through (d) represent different prior distributions (Fig. 2). To examine the sensitivity of these results to the scale of coefficients for the cost and benefit functions, Table 3 shows the results using smaller values for the coefficients for costs ($\gamma = 0.3$) and benefits ($\lambda = 1.8$). As expected from the results depicted in Fig. 5, the estimated economic value of a hypothetical 20-year research program is reduced with cost and benefit functions that exhibit smaller marginal changes. For example, the NPV under scenario (a) is decreased from $0.6 trillion (Table 2) to $0.4 trillion (Table 3). Overall, the value of a hypothetical 20-year research program is estimated at $0.5 trillion.

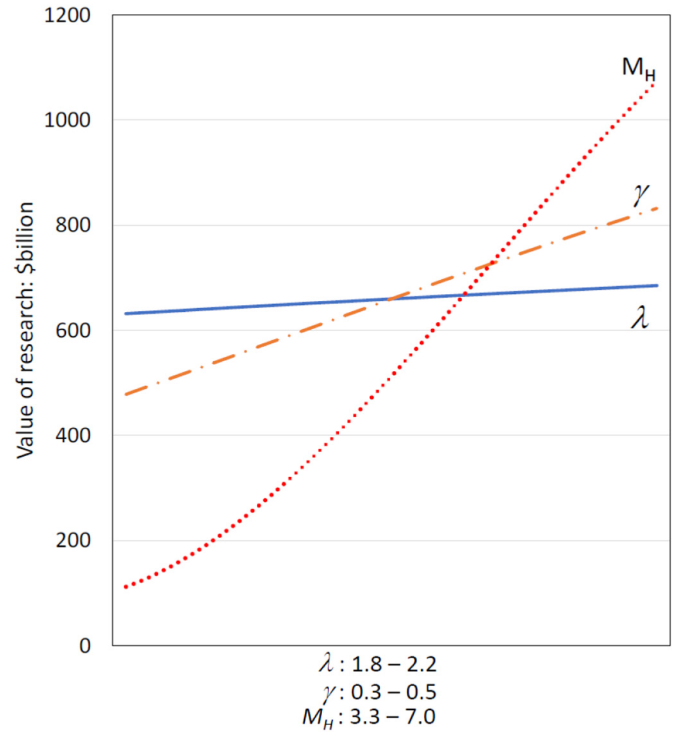

Fig. 5. Changing value of information with respect to model parameters. λ controls the marginal climate damage with respect to carbon emissions (q). γ controls the marginal benefit of economic output with respect to carbon emissions (q). M_H is the high-end estimate of BCP sequestration.

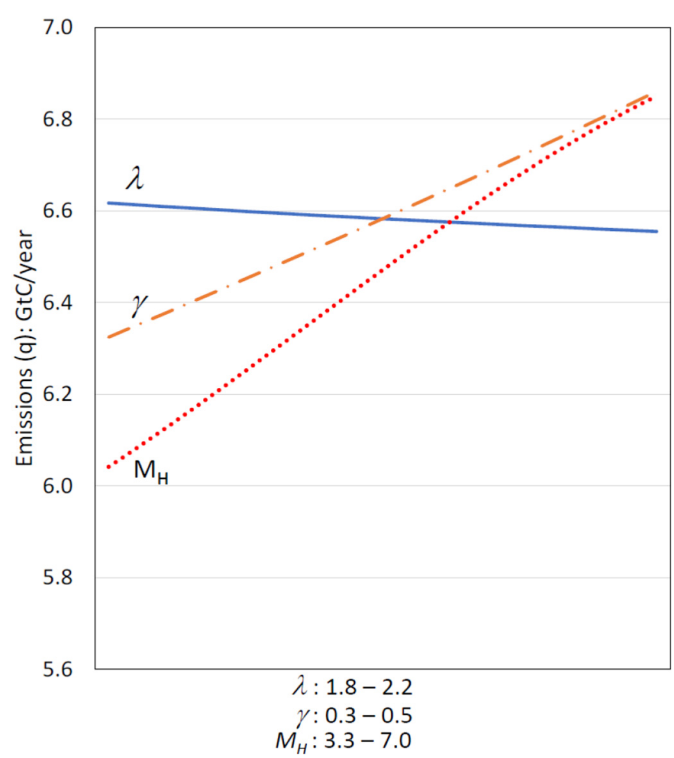

Fig. 6. Changing carbon emission target with respect to model parameters. λ controls the marginal climate damage with respect to carbon emissions (q). γ controls the marginal benefit of economic output with respect to carbon emissions (q). M_H is the high-end estimate of BCP sequestration.

[17] For detailed simulation results, see Appendix 2.

[18] As in a financial analysis, the discount rate is a critical component of the discounted cash flow calculation, and it determines how much a series of future cash flows is worth as a single lump sum value today. The discount rate is affected by both time preference and future economic growth. In cost-benefit analysis, a higher discount rate implies that the decision-maker has taken on a more near-term perspective. In contrast, a lower discount rate would suggest that the decision-maker has adopted a longer term perspective. The discount rates for public and private analyses often are different. Typically, in evaluating social and environmental programs, a lower discount rate is used, placing a greater value on the welfare of future generations.

Table 2
Incremental values with respect to precision and net present values of a hypothetical 20-year research program (cost, benefit function baselines: $\gamma = 0.4$, $\lambda = 2.0$).

Precision	Incremental value (current $billion)				Year	Incremental value (discounted $ billion)			
a	a	b	c	d		a	b	c	d
5	568.55	317.52	325.86	280.92	5	490.44	273.89	281.09	242.33
6	20.28	16.19	21.07	17.36	6	16.98	13.56	17.65	14.54
7	15.19	13.08	16.97	14.20	7	12.35	10.63	13.79	11.54
8	11.70	10.84	14.03	11.88	8	9.23	8.55	11.08	9.38
9	9.19	9.16	11.84	10.12	9	7.04	7.02	9.07	7.76
10	7.32	7.86	10.16	8.75	10	5.45	5.85	7.56	6.51
11	5.89	6.83	8.82	7.65	11	4.26	4.93	6.38	5.53
12	4.78	6.00	7.75	6.76	12	3.35	4.21	5.44	4.74
13	3.89	5.32	6.87	6.02	13	2.65	3.62	4.68	4.10
14	3.18	4.75	6.14	5.41	14	2.10	3.14	4.06	3.57
15	2.59	4.27	5.53	4.88	15	1.66	2.74	3.55	3.13
16	2.11	3.86	5.00	4.43	16	1.31	2.41	3.12	2.76
17	1.70	3.51	4.55	4.04	17	1.03	2.12	2.75	2.45
18	1.36	3.21	4.16	3.71	18	0.80	1.88	2.45	2.18
19	1.07	2.94	3.82	3.41	19	0.61	1.68	2.18	1.95
20	0.82	2.71	3.52	3.15	20	0.45	1.50	1.95	1.75
					NPV	559.73	347.74	376.79	324.22

Parameter *a* changing from 5 to 20 represents a reduction in coefficient of variation (standard deviation/mean) from 0.29 to 0.15.
Parameters for the prior distribution: (a) $\alpha = \beta = 1$; (b) $\alpha = 2, \beta = 3$; (c) $\alpha = 3, \beta = 2$; and (d) $\alpha = 3, \beta = 3$ (see Fig. 2).
Discount rate $\delta = 0.03$.

5. Conclusions

Considerable uncertainty exists regarding the sequestration of carbon via the BCP. Understanding the value of marine scientific research to reduce this uncertainty is important to policy makers and to the public. An analytical model of global carbon emission controls under scientific uncertainty was developed to characterize the economic value of such research. In the model, the amount of carbon sequestered in the ocean ranged from low- to high-end estimates. The model results supported the conclusion based upon optimality conditions that if BCP sequestration is low, then carbon emission levels also must be targeted to lower levels. The difference between the optimal levels of carbon emissions both with and without marine scientific research resulted in a difference in net economic benefits. This difference is a measure of the value of research on the BCP. Using a Bayesian approach, the value of information was estimated *ex ante*.

The model was illustrated using numerical simulations. The simulation results clearly showed that the value of research depended upon prior knowledge about BCP sequestration. This research value was positively related to the level of uncertainty, and it was at its highest when the prior was uniformly distributed. As expected, regardless of the level of prior knowledge, diminishing returns with respect to the level of research investment should be expected. Generally, the estimate of the value of information was on the order of hundreds of billions of dollars (around $0.5 trillion, roughly the GDP of Thailand or Sweden (IMF, 2019)), depending on the accuracy of prediction, the curvatures of the damage and benefit functions, and the range of uncertainty. This value also reveals the potential cost of policy makers ignoring new scientific knowledge on the biological carbon pump, if the information were available.

The analytical framework is applicable to other types of climate uncertainties. Results of scientific research value studies would enable governments to prioritize research alternatives and funding levels.

Table 3
Incremental values with respect to precision and net present values of a hypothetical 20-year research program (cost, benefit function sensitivities: $\gamma = 0.3$, $\lambda = 1.8$).

Precision	Incremental value (current $billion)				Year	Incremental value (discounted $billion)			
a	a	b	c	d		a	b	c	d
5	400.05	227.63	235.60	202.98	5	345.09	196.35	203.23	175.09
6	14.71	11.98	15.21	12.77	6	12.32	10.03	12.74	10.69
7	11.22	9.77	12.36	10.53	7	9.12	7.94	10.05	8.56
8	8.80	8.17	10.30	8.88	8	6.95	6.45	8.13	7.01
9	7.05	6.95	8.76	7.62	9	5.40	5.33	6.72	5.84
10	5.73	6.01	7.57	6.63	10	4.27	4.47	5.63	4.93
11	4.72	5.26	6.62	5.84	11	3.41	3.80	4.78	4.22
12	3.92	4.65	5.86	5.19	12	2.75	3.26	4.11	3.64
13	3.29	4.15	5.22	4.65	13	2.24	2.83	3.56	3.17
14	2.77	3.73	4.70	4.20	14	1.83	2.47	3.10	2.77
15	2.34	3.38	4.25	3.81	15	1.50	2.17	2.73	2.45
16	1.98	3.07	3.87	3.48	16	1.23	1.91	2.41	2.17
17	1.68	2.81	3.54	3.19	17	1.01	1.70	2.14	1.93
18	1.42	2.58	3.25	2.94	18	0.83	1.51	1.91	1.73
19	1.20	2.38	3.00	2.72	19	0.69	1.36	1.71	1.55
20	1.01	2.20	2.78	2.52	20	0.56	1.22	1.54	1.40
					NPV	399.21	252.81	274.49	237.14

Parameter *a* changing from 5 to 20 represents a reduction in the coefficient of variation (standard deviation/mean) from 0.29 to 0.15.
Parameters for the prior distribution: (a) $\alpha = \beta = 1$; (b) $\alpha = 2, \beta = 3$; (c) $\alpha = 3, \beta = 2$; and (d) $\alpha = 3, \beta = 3$ (see Fig. 2).
Discount rate $\delta = 0.03$.

List of symbols

W	social welfare function
U	utility
C	annual consumption
Y	annual gross economic output less investment
D	annual climate damage
N	annual growth in carbon concentration in the atmosphere
N_0	stock of carbon in the atmosphere at the beginning of the year
q	annual carbon emission target
L	annual carbon sequestered on land
M_L	annual carbon sequestered in ocean low estimate
M_H	annual carbon sequestered in ocean high estimate
z	range of uncertainty in annual ocean carbon sequestration
ρ	stochastic variable associated with annual ocean carbon sequestration
θ	coefficient of economic output function
ω	coefficient of economic output function
γ	coefficient of economic output function
η	coefficient of climate damage function
λ	coefficient of climate damage function

CRediT authorship contribution statement

Di Jin: Conceptualization, Methodology, Writing - original draft. **Porter Hoagland:** Conceptualization, Data curation, Investigation, Writing - original draft, Writing - review & editing. **Ken O. Buesseler:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Author names: Di Jin, Porter Hoagland, Ken O. Buesseler.

Acknowledgements

This research is supported by WHOI's Ocean Twilight Zone program which is part of the Audacious Project, a collaborative endeavor, housed at TED. DJ was also funded by National Oceanic and Atmospheric Administration (NOAA) Cooperative Institutes (CINAR) award NA14OAR4320158. KB was also funded by National Aeronautics and Space Administration (NASA) as part of the EXport Processes in the Ocean from RemoTe Sensing (EXPORTS) program award 80NSSC17K0555. We thank Ankur Shah for research assistance and three anonymous reviewers for their constructive suggestions.

Appendix 1. A brief description of the DICE model

The DICE model[19] is based on the theory of optimal economic growth (Ramsey, 1928). The basic idea is to choose policies that maximize the social welfare, i.e., to maximize the sum of discounted social welfare over time $t = 1, \ldots, T$:

$$W = \sum_{t=1}^{T} \frac{U[c(t), L(t)]}{(1+\delta)^t} \tag{1}$$

where U is the welfare function, c is per capita consumption, L is population, and δ is the pure rate of social time preference. Per capita consumption (c) equals net economic output (Q) minus investment (I) divided by population:

$$c(t) = \frac{C(t)}{L(t)} = \frac{Q(t)-I(t)}{L(t)}. \tag{2}$$

Net economic output (Q) is gross output net of damages and abatement:

$$Q(t) = \Omega(t)[1-\Lambda(t)]Y[A(t), K(t), L(t)] \tag{3}$$

where Y is the gross economic production output which is a function of production technology (A), capital (K) which is a function of investment (I), and labor (L). The factor capturing damages associated with climate change ($\Omega < 1$) is a function of global mean temperature (T_{AT}) which in turn is a function of carbon in the atmosphere (M_{AT}):

$$\Omega = f_1\{T_{AT}[M_{AT}(t)]\}. \tag{4}$$

The factor representing abatement ($\Lambda \le 1$) is a function of emission reduction rate (μ):

$$\Lambda = f_2[\mu(t)]. \tag{5}$$

Thus, the effects of both climate damage and abatement are modeled as fractions of the gross output (Y), in other words, the gross output is reduced due to climate change. Note that the emission reduction rate (μ) is a policy (control) variable in the model and determined by the optimization. Society chooses the optimal level of emission reduction to maximize welfare.

Global total carbon emissions are the sum of emissions from economic production and land-use activities. The emission from economic production is a function of output (Y) and emission reduction rate (μ).

$$N(t) = f_3[Y(t), \mu(t)] + N_{Land}(t) \tag{6}$$

The carbon cycle is modeled as:

$$M_{AT}(t) = \phi_{01}N(t) + \phi_{11}M_{AT}(t-1) + \phi_{21}M_{UP}(t-1) \tag{7}$$

$$M_{UP}(t) = \phi_{12}M_{AT}(t-1) + \phi_{22}M_{UP}(t-1) + \phi_{32}M_{LO}(t-1) \tag{8}$$

$$M_{LO}(t) = \phi_{23}M_{UP}(t-1) + \phi_{33}M_{LO}(t-1) \tag{9}$$

where M_{AT}, M_{UP}, and M_{LO} denote carbon in the atmosphere, carbon in the upper oceans and biosphere, and carbon in the deep ocean, and ϕs are coefficients.

The social cost of carbon (SCC) is calculated using the optimization results:

$$SCC(t) = \frac{\partial W/\partial N(t)}{\partial W/\partial C(t)} = -\frac{\partial C(t)}{\partial N(t)} \tag{10}$$

where $\partial W/\partial N$ (<0) is the marginal welfare change with respect to carbon emissions, and $\partial W/\partial C$ is the marginal welfare change with respect to consumption. So the SCC is carbon emission impact in terms of a reduction in consumption.

Appendix 2. Results of sensitivity analysis

Fig. 1A presents a similar set of plots in Fig. 2 under a more accurate prediction. Because of the improvement in precision, the variances of the likelihood and posterior pdfs are smaller than those of the other distributions in Fig. 2.

Figs. 2A and 3A show the results of sensitivity analysis with respect to parameters γ and λ. Fig. 4A illustrates the effect of changing the high-end estimate of BCP sequestration (M_H). Apparently, a positive relationship exists between the research value and the level of uncertainty, and the value is very sensitive with respect to z.

[19] For details, see Nordhaus (1993, 2010, 2017) and Nordhaus and Sztorc (2013).

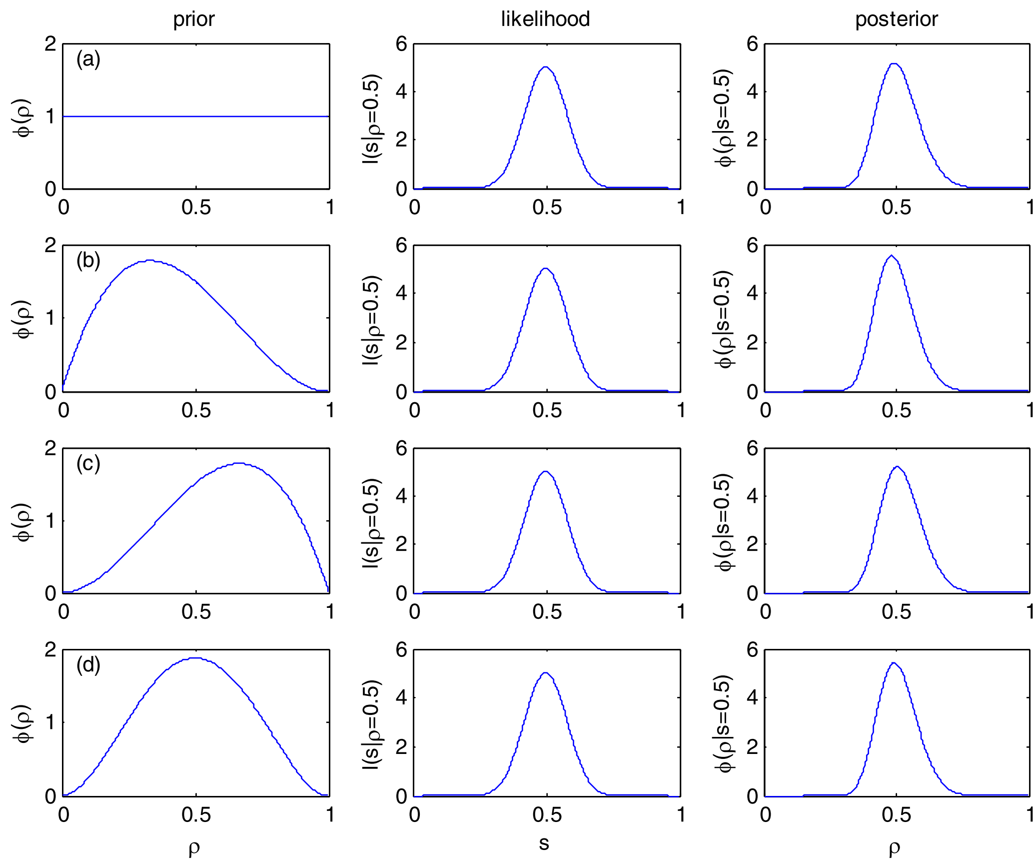

Fig. 1A. Prior, likelihood, and posterior ($a = 20$). (a) $\alpha = \beta = 1$; (b) $\alpha = 2, \beta = 3$; (c) $\alpha = 3, \beta = 2$; and (d) $\alpha = 3, \beta = 3$.

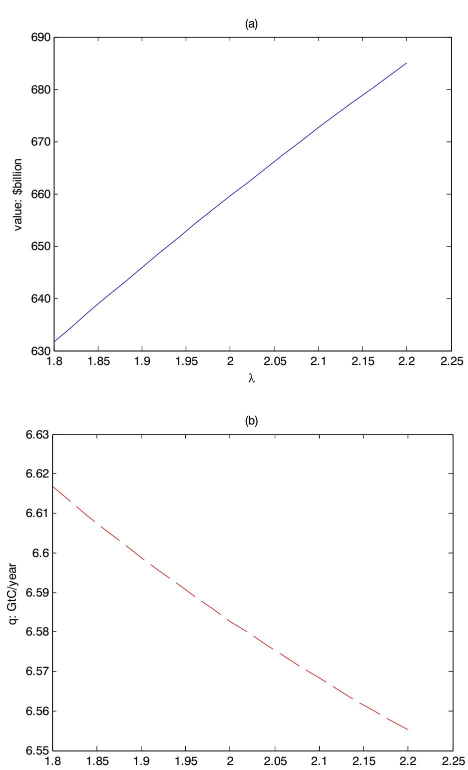

Fig. 2A. Effects of changing λ (marginal change in damage).

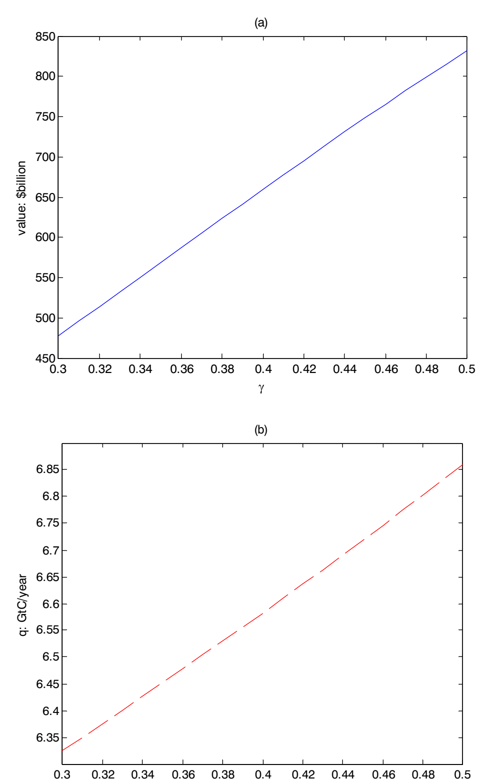

Fig. 3A. Effects of changing γ (marginal change in output).

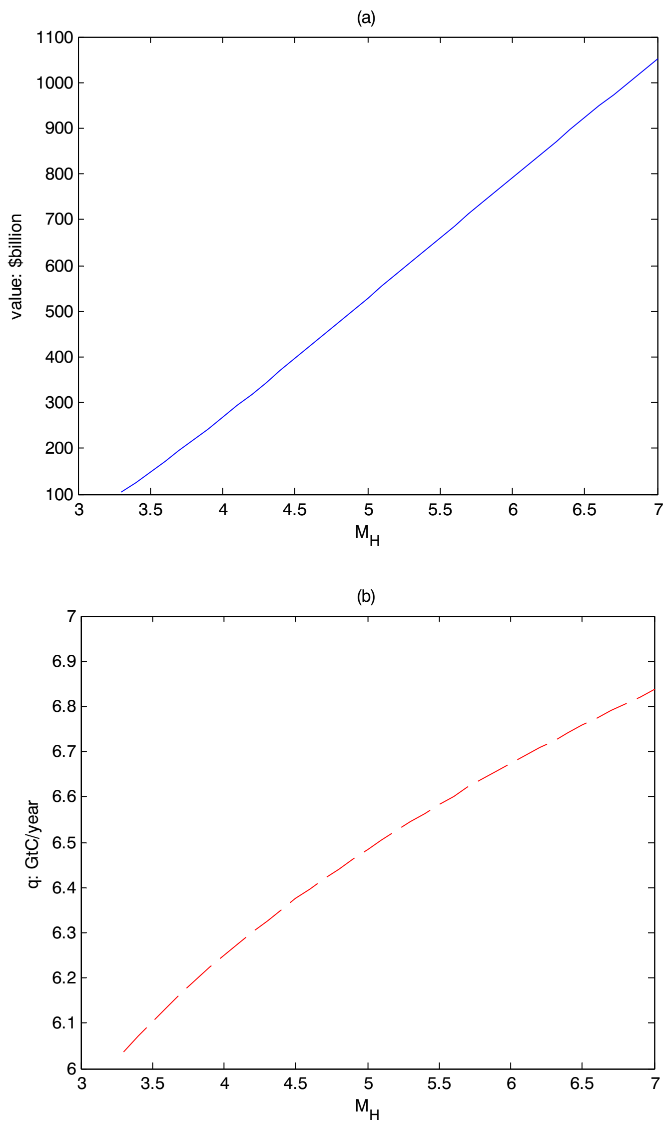

Fig. 4A. Effects of changing the range of uncertainty.

References

Adams, R.M., Bryant, K.J., Mccarl, B.A., Legler, D.M., O'Brien, J., Solow, A., Weiher, R., 1995. Value of improved long-range weather information. Contemp. Econ. Policy 13, 10–19. https://doi.org/10.1111/j.1465-7287.1995.tb00720.x.

Antia, A.N., Koeve, W., Fischer, G., Blanz, T., Schulz-Bull, D., Schölten, J., Neuer, S., Kremling, K., Kuss, J., Peinert, R., Hebbeln, D., Bathmann, U., Conte, M., Fehner, U., Zeitzschel, B., 2001. Basin-wide particulate carbon flux in the Atlantic Ocean: regional export patterns and potential for atmospheric CO2 sequestration. Glob. Biogeochem. Cycles 15, 845–862. https://doi.org/10.1029/2000GB001376.

Armstrong, R.A., Lee, C., Hedges, J.I., Honjo, S., Wakeham, S.G., 2001. A new, mechanistic model for organic carbon fluxes in the ocean based on the quantitative association of POC with ballast minerals. Deep Sea Research Part II: Topical Studies in Oceanography, the US JGOFS Synthesis and Modeling Project: Phase 1. vol. 49, pp. 219–236. https://doi.org/10.1016/S0967-0645(01)00101-1.

Auffhammer, M., 2018. Quantifying economic damages from climate change. J. Econ. Perspect. 32, 33–52. https://doi.org/10.1257/jep.32.4.33.

Barange, M., Butenschön, M., Yool, A., Beaumont, N., Fernandes, J.A., Martin, A.P., Allen, J.I., 2017. The cost of reducing the North Atlantic Ocean biological carbon pump. Front. Mar. Sci. 3. https://doi.org/10.3389/fmars.2016.00290.

Bernknopf, R.L., Brookshire, D.S., McKee, M., Soller, D.R., 1997. Estimating the social value of geologic map information: a regulatory application. J. Environ. Econ. Manag. 32, 204–218. https://doi.org/10.1006/jeem.1996.0963.

Bianchi, D., Stock, C., Galbraith, E.D., Sarmiento, J.L., 2013. Diel vertical migration: ecological controls and impacts on the biological pump in a one-dimensional ocean model. Glob. Biogeochem. Cycles 27, 478–491. https://doi.org/10.1002/gbc.20031.

Bickel, P.J., Doksum, K.A., 2001. Mathematical Statistics: Basic Ideas and Selected Topics. 2nd edition. vol I. Prentice-Hall, Upper Saddle River, N.J 2nd Edition.

Bopp, L., Monfray, P., Aumont, O., Dufresne, J.-L., Treut, H.L., Madec, G., Terray, L., Orr, J.C., 2001. Potential impact of climate change on marine export production. Glob. Biogeochem. Cycles 15, 81–99. https://doi.org/10.1029/1999GB001256.

Boyd, P.W., 2015. Toward quantifying the response of the oceans' biological pump to climate change. Front. Mar. Sci. 2. https://doi.org/10.3389/fmars.2015.00077.

Boyd, P.W., Trull, T.W., 2007. Understanding the export of biogenic particles in oceanic waters: is there consensus? Prog. Oceanogr. 72, 276–312. https://doi.org/10.1016/j.pocean.2006.10.007.

Boyd, P.W., Claustre, H., Levy, M., Siegel, D.A., Weber, T., 2019. Multi-faceted particle pumps drive carbon sequestration in the ocean. Nature 568, 327–335. https://doi.org/10.1038/s41586-019-1098-2.

Buesseler, K.O., Lamborg, C.H., Boyd, P.W., Lam, P.J., Trull, T.W., Bidigare, R.R., Bishop, J.K.B., Casciotti, K.L., Dehairs, F., Elskens, M., Honda, M., Karl, D.M., Siegel, D.A., Silver, M.W., Steinberg, D.K., Valdes, J., Mooy, B.V., Wilson, S., 2007. Revisiting carbon flux through the ocean's twilight zone. Science 316, 567–570. https://doi.org/10.1126/science.1137959.

Cooke, R., Wielicki, B.A., Young, D.F., Mlynczak, M.G., 2014. Value of information for climate observing systems. Environ Syst Decis 34, 98–109. https://doi.org/10.1007/s10669-013-9451-8.

Cooke, R., Golub, A., Wielicki, B.A., Young, D.F., Mlynczak, M.G., Baize, R.R., 2017. Using the social cost of carbon to value earth observing systems. Clim. Pol. 17, 330–345. https://doi.org/10.1080/14693062.2015.1110109.

Costello, C., Rassweiler, A., Siegel, D., Leo, G.D., Micheli, F., Rosenberg, A., 2010. The value of spatial information in MPA network design. PNAS 107, 18294–18299. https://doi.org/10.1073/pnas.0908057107.

Freeman, Mark C., Groom, Ben, Zeckhauser, Richard J., 2015. Better predictions, better allocations: scientific advances and adaptation to climate change. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 373, 20150122. https://doi.org/10.1098/rsta.2015.0122.

Henson, S.A., Sanders, R., Madsen, E., Morris, P.J., Moigne, F.L., Quartly, G.D., 2011. A reduced estimate of the strength of the ocean's biological carbon pump. Geophys. Res. Lett. 38. https://doi.org/10.1029/2011GL046735.

Henson, S., Le Moigne, F., Giering, S., 2019. Drivers of carbon export efficiency in the global ocean. Glob. Biogeochem. Cycles 33, 891–903. https://doi.org/10.1029/2018GB006158.

Hofmann, M., Schellnhuber, H.-J., 2009. Oceanic acidification affects marine carbon pump and triggers extended marine oxygen holes. PNAS 106, 3017–3022. https://doi.org/10.1073/pnas.0813384106.

Hope, Chris, 2015. The $10 trillion value of better information about the transient climate response. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 373, 20140429. https://doi.org/10.1098/rsta.2014.0429.

Hsiang, S., Kopp, R.E., 2018. An economist's guide to climate change science. J. Econ. Perspect. 32, 3–32. https://doi.org/10.1257/jep.32.4.3.

IMF, 2019. World Economic Outlook Database, October 2019. International Monetary Fund https://www.imf.org/external/pubs/ft/weo/2019/02/weodata/index.aspx.

Inniss, L., Simcock, A. (Eds.), 2016. The First Global Integrated Marine Assessment: World Ocean Assessment I. New York: UN General Assembly, Regular Process for Global Reporting and Assessment of the State of the Marine Environment, Including Socio-economic Aspects.

IPCC, 2019. Chapter 5: changing ocean, marine ecosystems, and dependent communities. In: Pörtner, H.-O., Roberts, D.C., Masson-Delmotte, V., Zhai, P., Tignor, M., Poloczanska, E., Mintenbeck, K., Nicolai, M., Okem, A., Petzold, J., Rama, B., Weyer, N. (Eds.), IPCC Special Report on the Ocean and Cryosphere in a Changing Climate https://www.ipcc.ch/srocc/home/.

Isensee, K., Horn, L., Schaaper, M., 2017. The funding for ocean science. In: Valdés, L., et al. (Eds.), Global Ocean Science Report—The Current Status of Ocean Science Around the World. IOC-UNESCO, Paris, pp. 80–97.

Jin, D., Hoagland, P., 2008. The value of harmful algal bloom predictions to the nearshore commercial shellfish fishery in the Gulf of Maine. Harmful Algae 7, 772–781. https://doi.org/10.1016/j.hal.2008.03.002.

Jin, D., Hoagland, P., Solow, A., 2006. The economic value of environmental research in understanding the relative contributions of sources of nutrients to coastal waters. Nat. Resour. Model. 19, 201–219. https://doi.org/10.1111/j.1939-7445.2006.tb00180.x.

Jónasdóttir, S.H., Visser, A.W., Richardson, K., Heath, M.R., 2015. Seasonal copepod lipid pump promotes carbon sequestration in the deep North Atlantic. PNAS 112, 12122–12126. https://doi.org/10.1073/pnas.1512110112.

Khatiwala, S., Tanhua, T., Mikaloff Fletcher, S., Gerber, M., Doney, S.C., Graven, H.D., Gruber, N., McKinley, G.A., Murata, A., Ríos, A.F., Sabine, C.L., 2013. Global ocean storage of anthropogenic carbon. Biogeosciences 10, 2169–2191. https://doi.org/10.5194/bg-10-2169-2013.

Kite-Powell, H.L., Solow, A.R., 1994. A Bayesian approach to estimating benefits of improved forecasts. Meteorol. Appl. 1, 351–354. https://doi.org/10.1002/met.5060010405.

Klaas, C., Archer, D.E., 2002. Association of sinking organic matter with various types of mineral ballast in the deep sea: implications for the rain ratio. Glob. Biogeochem. Cycles 16. https://doi.org/10.1029/2001GB001765 (63-1-63–14).

Kwon, E.Y., Primeau, F., Sarmiento, J.L., 2009. The impact of remineralization depth on the air–sea carbon balance. Nat. Geosci. 2, 630–635. https://doi.org/10.1038/ngeo612.

Lave, L.B., 1963. The value of better weather information to the raisin industry. Econometrica 31, 151–164. https://doi.org/10.2307/1910954.

Laws, E.A., Falkowski, P.G., Smith, W.O., Ducklow, H., McCarthy, J.J., 2000. Temperature effects on export production in the open ocean. Glob. Biogeochem. Cycles 14, 1231–1246. https://doi.org/10.1029/1999GB001229.

Le Moigne, F.A.C., 2019. Pathways of organic carbon downward transport by the oceanic biological carbon pump. Front. Mar. Sci. 6. https://doi.org/10.3389/fmars.2019.00634.

Le Quéré, C., Andrew, R.M., Friedlingstein, P., Sitch, S., Hauck, J., Pongratz, J., Pickers, P.A., Korsbakken, J.I., Peters, G.P., Canadell, J.G., Arneth, A., Arora, V.K., Barbero, L., Bastos, A., Bopp, L., Chevallier, F., Chini, L.P., Ciais, P., Doney, S.C., Gkritzalis, T., Goll, D.S., Harris, I., Haverd, V., Hoffman, F.M., Hoppema, M., Houghton, R.A., Hurtt, G., Ilyina, T., Jain, A.K., Johannessen, T., Jones, C.D., Kato, E., Keeling, R.F., Goldewijk, K.K., Landschützer, P., Lefèvre, N., Lienert, S., Liu, Z., Lombardozzi, D., Metzl, N., Munro, D.R., Nabel, J.E.M.S., Nakaoka, S., Neill, C., Olsen, A., Ono, T., Patra, P., Peregon, A., Peters, W., Peylin, P., Pfeil, B., Pierrot, D., Poulter, B., Rehder, G., Resplandy, L., Robertson, E., Rocher, M., Rödenbeck, C., Schuster, U., Schwinger, J., Séférian, R., Skjelvan, I., Steinhoff, T., Sutton, A., Tans, P.P., Tian, H., Tilbrook, B., Tubiello, F.N., Laan-Luijkx, I.T. van der, Werf, G.R. van der, Viovy, N., Walker, A.P., Wiltshire, A.J., Wright, R., Zaehle, S., Zheng, B., 2018. Global carbon budget 2018. Earth System Science Data 10, 2141–2194. https://doi.org/10.5194/essd-10-2141-2018.

Le Quéré, C., Jackson, R.B., Jones, M.W., Smith, A.J.P., Abernethy, S., Andrew, R.M., De-Gol, A.J., Willis, D.R., Shan, Y., Canadell, J.G., Friedlingstein, P., Creutzig, F., Peters, G.P., 2020. Temporary reduction in daily global CO2 emissions during the COVID-19 forced confinement. Nat. Clim. Chang., 1–7 https://doi.org/10.1038/s41558-020-0797-x.

Levy, M., Bopp, L., Karleskind, P., Resplandy, L., Ethe, C., Pinsard, F., 2013. Physical pathways for carbon transfers between the surface mixed layer and the ocean interior. Glob. Biogeochem. Cycles 27, 1001–1012. https://doi.org/10.1002/gbc.20092.

Lindoso, V., 2019. Choices Made Now Are Critical for the Future of Our Ocean and Cryosphere. IOC-UNESCO, Paris Last accessed on 6 October 2019 at. https://en.unesco.org/news/choices-made-now-are-critical-future-our-ocean-and-cryosphere.

Manizza, M., Buitenhuis, E.T., Quéré, C.L., 2010. Sensitivity of global ocean biogeochemical dynamics to ecosystem structure in a future climate. Geophys. Res. Lett. 37. https://doi.org/10.1029/2010GL043360.

Marsay, C.M., Sanders, R.J., Henson, S.A., Pabortsava, K., Achterberg, E.P., Lampitt, R.S., 2015. Attenuation of sinking particulate organic carbon flux through the mesopelagic ocean. PNAS 112, 1089–1094. https://doi.org/10.1073/pnas.1415311112.

Martin, J.H., Knauer, G.A., Karl, D.M., Broenkow, W.W., 1987. VERTEX: carbon cycling in the northeast Pacific. Deep Sea Research Part A. Oceanographic Research Papers 34, 267–285. https://doi.org/10.1016/0198-0149(87)90086-0.

Matsumoto, K., Tokos, K., Chikamoto, M., Ridgwell, A., 2010. Characterizing post-industrial changes in the ocean carbon cycle in an Earth system model. Tellus Ser. B Chem. Phys. Meteorol. 62, 296–313. https://doi.org/10.1111/j.1600-0889.2010.00461.x.

Nordhaus, W.D., 1993. Rolling the 'DICE': an optimal transition path for controlling greenhouse gases. Resour. Energy Econ. 15, 27–50. https://doi.org/10.1016/0928-7655(93)90017-O.

Nordhaus, W.D., 2010. Economic aspects of global warming in a post-Copenhagen environment. PNAS 107, 11721–11726. https://doi.org/10.1073/pnas.1005985107.

Nordhaus, W.D., 2017. Revisiting the social cost of carbon. PNAS 114, 1518–1523. https://doi.org/10.1073/pnas.1609244114.

Nordhaus, W., Sztorc, P., 2013. DICE 2013R: Introduction and User's Manual. 2nd edition. http://www.econ.yale.edu/~nordhaus/homepage/homepage/documents/DICE_Manual_100413r1.pdf.

Palevsky, H.I., Doney, S.C., 2018. How choice of depth horizon influences the estimated spatial patterns and global magnitude of ocean carbon export flux. Geophys. Res. Lett. 45, 4171–4179. https://doi.org/10.1029/2017GL076498.

Peck, S.C., Teisberg, T.J., 1993. Global warming uncertainties and the value of information: an analysis using CETA. Resour. Energy Econ. 15, 71–97. https://doi.org/10.1016/0928-7655(93)90019-Q.

Pindyck, R.S., 2012. Uncertain outcomes and climate change policy. J. Environ. Econ. Manag. 63 (3), 289–303. https://doi.org/10.1016/j.jeem.2011.12.001.

Primeau, F., 2005. Characterizing transport between the surface mixed layer and the ocean interior with a forward and adjoint global ocean transport model. J. Phys. Oceanogr. 35, 545–564. https://doi.org/10.1175/JPO2699.1.

Ramsey, F.P., 1928. A mathematical theory of saving. Econ. J. 38, 543–559. https://doi.org/10.2307/2224098.

Sanders, R., Henson, S.A., Koski, M., De La Rocha, C.L., Painter, S.C., Poulton, A.J., Riley, J., Salihoglu, B., Visser, A., Yool, A., Bellerby, R., Martin, A.P., 2014. The biological carbon pump in the North Atlantic. Progress in Oceanography, North Atlantic Ecosystems, the Role of Climate and Anthropogenic Forcing on Their Structure and Function. vol. 129, pp. 200–218. https://doi.org/10.1016/j.pocean.2014.05.005.

Schimmelpfennig, D.E., Norton, G.W., 2003. What is the value of agricultural economics research? Am. J. Agric. Econ. 85, 81–94. https://doi.org/10.1111/1467-8276.00104.

Siegel, D.A., Buesseler, K.O., Behrenfeld, M.J., Benitez-Nelson, C.R., Boss, E., Brzezinski, M.A., Burd, A., Carlson, C.A., D'Asaro, E.A., Doney, S.C., Perry, M.J., Stanley, R.H.R., Steinberg, D.K., 2016. Prediction of the export and fate of global ocean net primary production: the EXPORTS science plan. Front. Mar. Sci. 3. https://doi.org/10.3389/fmars.2016.00022.

Stukel, M.R., Song, H., Goericke, R., Miller, A.J., 2018. The role of subduction and gravitational sinking in particle export, carbon sequestration, and the remineralization length scale in the California current ecosystem. Limnol. Oceanogr. 63, 363–383. https://doi.org/10.1002/lno.10636.

Taucher, J., Bach, L.T., Riebesell, U., Oschlies, A., 2014. The viscosity effect on marine particle flux: a climate relevant feedback mechanism. Glob. Biogeochem. Cycles 28, 415–422. https://doi.org/10.1002/2013GB004728.

United Nations Statistics Division (UNSD), 2019. Sustainable development goals. Last accessed on 6 October 2019 at. https://unstats.un.org/sdgs/indicators/database/.

Villa-Alfageme, M., Soto, F.C. de, Ceballos, E., Giering, S.L.C., Moigne, F.A.C.L., Henson, S., Mas, J.L., Sanders, R.J., 2016. Geographical, seasonal, and depth variation in sinking particle speeds in the North Atlantic. Geophys. Res. Lett. 43, 8609–8616. https://doi.org/10.1002/2016GL069233.