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Evaluation of the ocean ecosystem: climate change modelling with backstop technology

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Abstract

This paper discusses the economic impacts of climate change, including those on ecosystems, and whether a new backstop technology should be used under conditions of strict temperature targets. Using the dynamic integrated climate-economy (DICE) model, we developed a new model to calculate the optimal path by considering new backstop technologies, such as CO₂ capture and storage (CCS). We identify the effects of parameter changes based on the resulting differences in CO₂ leakage and sites, and we analyse the feasibility of CCS. In addition, we focus on ocean acidification and consider the impact on economic activity. As a result, when CCS is assumed to carry a risk of CO₂ leakage and acidification is considered to result in a decrease in utility, we find that CCS can only delay the effects of climate change, but its use is necessary to achieve strict targets, such as a 1.5 °C limit. This observation suggests that if the target temperature is too tight, we might end up employing a technology that sacrifices the ecosystem too greatly.

Keywords: climate change; ocean acidification; economic impact; CCS; CEEM

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1 Introduction

The possibility of global warming began to be considered near the end of the 20th century, and global warming is now recognized as a problem throughout the world. In 1992, the United Nations Conference on Environment and Development (UNCED) was held in Rio de Janeiro, and the United Nations Framework Convention on Climate Change (UNFCCC) was adopted. The Intergovernmental Panel on Climate Change (IPCC) recommended that the average temperature increase should be kept to less than 2 degrees in the IPCC Fifth Assessment Report (Stocker et al., 2013). Moreover, a 1.5-degree limit was cited as a target at the 2015 United Nations Climate Change Conference (COP21) held in Paris in 2015.

The impacts of increasing temperature have been analysed by many researchers (Leemans and Eickhout, 2004; Warren et al., 2006, 2011). Recently, it has been reported that an increase in the average temperature is associated with climatic drought risks (Vicente-Serrano et al., 2014), coastal flood risks (Hinkel et al., 2014) and human health risks (Hajat et al., 2014; Komen et al., 2015). Parry et al. (2001) noted that the various risks increase rapidly when the temperature increase is approximately 1.5 - 2 degrees. Warren (2006) warned of the impacts of an increasing average temperature on the ecosystem. It was suggested that a 1-degree increase in temperature may induce a 10% ecosystem transformation and a loss in cereal production of 20 to 35 million tons, that a 2-degree increase in temperature may induce a 97% loss of coral reefs, and so forth. Moreover, few ecosystems may be able to adapt to an increase in temperature of more than 3 degrees. These risks are present, and we must take measures to rapidly mitigate or adapt to them.

In addition to evaluations of the individual risks, integrated evaluations of climate change have been presented. Cline (1992a,b) conducted a cost-benefit analysis of climate change, considering environmental loss, human life, disasters, water supply, and so forth. Based on the results of this analysis, Cline concluded that an aggressive policy that would require cut-backs of 70% of predicted emission by the middle of this century can be justified. Moreover, Stern et al. (2006) claimed that the benefits of strong early action are greater than the costs

of no action.

By contrast, Nordhaus took a more optimistic stance on climatic change, based on his DICE model (Nordhaus, 1992). This model can comprehensively analyse economic impacts while considering dynamic CO₂ circulation ¹. The model indicates that long-term, continuous reduction of CO₂ emissions is preferable to a large, abrupt reduction in the near future.

The causes of these conflicting conclusions include the magnitude of the discount rate, the uncertainty or ambiguity of the parameters, and the irreversibility of climate change. The conservative stance of the DICE model is often criticized. Kaufmann (1997) reported that the DICE model contains unsupported assumptions, simple extrapolations, and mis-specifications and that it consequently underestimates the effects of climate change. The robustness of the DICE model with respect to ambiguity was assessed by Hu et al. (2012). Hu et al. observed that the ineffectiveness noted by Nordhaus is significantly increased when the ambiguity of distribution is considered but insisted that a lack of any emission control policies may carry a high risk and doing nothing is by no means a rational response. Other researchers have extended the DICE model in various directions to achieve greater realism. For example, De Bruin et al. (2009) developed the AD-DICE model by introducing adaptation as another control variable. The AD-DICE model can estimate the adaptation costs of climate change by splitting the net damages into residual damages and protection costs. The ENTICE model developed by Popp (2004, 2006) separates energy units from inputs and treats technological change as an endogenous variable. The uncertainty in the DICE model with regard to the level of damage caused by global warming was also analysed by Traeger (2014) and Crost and Traeger (2014). In addition to the DICE model, various other Integrated Assessment Models (IAMs) have also been developed. The features of these models have been summarized by Dowlatabadi (1995); Stanton et al. (2009).

These models, such as the DICE model, are classified among the welfare optimization type. Nevertheless, many IAMs use other methodologies; general equilibrium (Gerlagh, 2008),

¹ Nordhaus later improved the dynamic CO₂ circulation model and several functions of the DICE model and was able to calculate more realistic economic impacts (Nordhaus and Sztorc, 2013).

simulation (Dowlatabadi, 1998; Hinkel, 2005; Hope, 2006) and so forth. Welfare optimization models are simple yet transparent, making them suitable for the analysis of conceptual models. In addition, CCS technology investment is evaluated by using real option approach (Zhou et al., 2010; Zhu and Fan, 2011). Also CCS had been introduced to some energy-economic system models (Syri et al., 2008; Held et al., 2009).

This study focuses on the impact on ecosystems or the environment. The DICE model assumes that the technological costs of emission reduction will be reduced in the future by virtue of technical innovations. This assumption is not unsupportable, but new technologies will not necessarily bring only benefits. Some new technologies may carry unknown risks. For example, a mitigation technique known as CO₂ capture and storage (CCS) has recently been attracting attention. CCS is a method based on capturing waste CO₂, such as that from power plants, and transporting it to deep underground storage areas. According to Metz et al. (2005), CCS could reduce global emissions by 9-12% by 2020 and 21-45% by 2050. The GlobalCCSInstitute (2016) reports that in sectors with high-concentration gas streams (natural gas processing sector, ammonia/fertiliser production sector, bio-ethanol production sector, hydrogen production sector, iron and steel production sector), large-scale CO₂ capture projects are underway. Three principal types of capture technologies are used; pre-combustion, oxyfuel combustion, and post-combustion. These technologies have been analysed, and their impacts and efficiencies were reported (Koornneef et al., 2008; Li et al., 2009; Park et al., 2011). The optimal technology is selected and implemented according to the physical properties of CO₂ emitted from each emission source across several industries. For example, post-combustion technology is used to capture CO₂ in the cement industry (Cormos and Cormos, 2017), and with pre-combustion being used in industrial processes, such as natural gas(Kanniche et al., 2010) and oil (Weydahl et al., 2013). In addition, the technology of bio-energy with carbon capture and storage (BECCS)(Azar et al., 2010), which combines CCS technology in biomass power plants or biofuel manufacturing processes, has also attracted attention. The energy potential and cost-effectiveness of negative emissions

have been assessed by many researchers (Moreira et al., 2016; Bui et al., 2017). Chemical looping combustion process and calcium looping process have also been developed in recent years. These technologies have, potentially, much lower cost and much higher efficiency than other technologies (Lyngfelt et al., 2001; Fan et al., 2008; Zhu et al., 2015; Perejón et al., 2016).²

However, some researchers are concerned about the possibility of CO₂ leakage. Such leakage may cause local ocean acidification (Blackford et al., 2009) and may impact the biodiversity of marine life (Kroeker et al., 2013). Currently, CCS is still expensive, but its cost is expected to decrease to a feasible level in the future. At that time, it will be necessary to decide whether to adopt this technology. To determine the best among the possible technologies, it will be important to assess the effects that we may suffer from their unknown risks. Efforts have been made to perform comprehensive evaluations of CCS at the plant and macroeconomic levels (Viebahn et al., 2012, 2014, 2015; Pettinau et al., 2017; Sathre et al., 2012; Koelbl et al., 2016).

Moreover, we cannot overlook the potential damage to the ecosystem. Although we do not have a detailed picture of the services provided by the ecosystem and their value because of the complexity and vastness of the ecosystem, many researchers have presented estimates. For example, the value of ecosystem services as estimated by Costanza et al. (1997) and Balmford et al. (2002) is in the range of US\$ 16 - 54 trillion per year. Focusing on commercial value, Narita et al. (2012) reported that the global economic costs of mollusc loss from ocean acidification may be more than US\$ 100 billion if the mollusc demand increases with future income rise.

With these studies in mind, we attempt to determine whether technologies that reduce CO₂ but carry ecosystem pollution risks should be used under conditions of strict temperature targets. To address this question, we modify the DICE model accordingly and analyse the temperature targets. The three main contributions of this study can be summarized as

²Our research does not deal with the difference of technologies, but such differences are important and should be introduced into future models.

follows. The first contribution is a modification of the DICE model. By addressing several backstop technologies, we consider the possible effects of introducing technologies such as CCS. We show that the optimal choice of whether CCS should be used changes depending on the leakage ratio and the leakage sites. The second contribution is a consideration of the fact that if more people begin to feel that ocean acidification will result in a decrease in utility, then the optimal level of emission should be considerably less. This effect may result in a 0.5-degree decrease in the desired average temperature even if the direct effect on utility caused by acidification is less than 1% with respect to the consumption utility. The negative impacts of ocean acidification caused by CO₂ leakage have been recognized, and local impacts have been intensively investigated in laboratory-based, field, and natural experiments (Widdicombe and Spicer, 2008; Widdicombe et al., 2013; Murray et al., 2013; Ishida et al., 2013). The novelty of our work lies in providing an assessment of the potential of CCS as a mitigation technology at the global level, based on those seminal experimental works. Models that focus on CCS use have previously been developed (Mori, 2012; Lee, 2017), but these models do not consider ecosystem damage. Finally, we address policies that call for a 2-degree target and a 1.5-degree target. As discussed by Azar et al. (2006) and Scott et al. (2013), CCS is regarded as a core component of emission-reduction scenarios, and thus, it is important to evaluate the potential of CCS for reaching degree targets (Tollefson, 2015). Previous studies in this context include those of Azar et al. (2010) and Selosse and Ricci (2017). We contribute to the literature by explicitly modelling the negative impact of CO₂ leakage into the ocean and examining the simulated optimal plan at the global level. The results of our simulation analysis show that these targets are rather strict, and the social cost of carbon (SCC) becomes quite high in comparison with the optimal control case. However, if we must implement such a strict target, we will be required to use lower-cost technologies despite their potential risk to the environment.

This paper is structured as follows. Section 2 presents the DICE model and its theoretical framework. Then, in section 3, we present the simplest version of our dynamic integrated

climate-ecosystem-economy model (CEEM), introducing a backstop technology that can capture and store CO₂ but carries a risk of leakage into the atmosphere and ocean. We consider the harmful effects of this leakage from the perspective of ocean acidification in section 4, and we explore how the optimal solution is affected. Moreover, we analyse the 2-degree and 1.5-degree targets using our model. The last section presents our conclusions.

2 DICE model

Our model, the CEEM, is based on the DICE model. Therefore, we introduce the DICE model in detail in this section, and we describe the additional features (consideration of additional backstop technologies and the ocean ecosystem) incorporated into the CEEM in the following section.

The DICE model is a dynamic optimization model for analysing the effects of climate change. This model is primarily based on the Ramsey model, and the total utility to be maximized is represented by the following expression:

$$\sum_{t=1}^T U [c(t), L(t)] (1 + \rho)^{-t}, \quad (1)$$

$$U [c(t), L(t)] = L(t) \frac{[c(t)]^{1-\alpha}}{1 - \alpha},$$

where U is the utility, $L(t)$ is the labour in time period t , $c(t)$ is the flow of consumption per capita in period t , ρ is the discount rate and is assumed to be 0.3, and α is the elasticity of intertemporal substitution and is assumed to be 1.45. This optimization problem includes two sets of constraints: one represents economic constraints, and the other represents emission and carbon cycle constraints.

2.1 Economic constraints

First, let us consider the economic constraints. If $A(t)$, $K(t)$ and $L(t)$ denote the total factor productivity (TFP), capital and population, respectively, in period t , then the production $Q(t)$ is given by

$$Q(t) = Q_{net}(t) - \Lambda(t)A(t)K(t)^\gamma L(t)^{1-\gamma}, \quad (2)$$

$$Q_{net}(t) = A(t)K(t)^\gamma L(t)^{1-\gamma} [1 - \Omega(t)], \quad (3)$$

where γ is the elasticity of output with respect to capital and is assumed to be 0.3 and $\Lambda(t)$ and $\Omega(t)$ are the abatement cost ratio and the climate damage ratio, respectively. These two variables are given by

$$\Lambda(t) = \theta_1(t)p(t)\mu(t)^{\theta_2}, \quad (4)$$

$$\Omega(t) = \psi_1 T_{AT}(t) + \psi_2 [T_{AT}(t)]^2. \quad (5)$$

The abatement cost ratio, $\Lambda(t)$, represents the cost of emission reduction as determined by the emission control rate $\mu(t)$. $p(t)$ is the cost of the backstop technology, and $\theta_1(t)$ and θ_2 are parameters. θ_1 and θ_2 are assumed to be defined by the equation $\theta_1(t) = \sigma(t)/2800$ and to be equal to 2.8, respectively. Here, $\sigma(t)$ is the level of carbon intensity (mentioned below). The abatement cost is calculated based on the assumption that it is proportional to a power function of the reduction rate. Meanwhile, the climate damage ratio $\Omega(t)$ is expressed as a quadratic function of the atmospheric temperature $T_{AT}(t)$ and the parameters ψ_1 and ψ_2 . Tol (2009) estimated that a 3 °C increase in temperature will cause damage equivalent to approximately 3% of the global output. However, this estimate ignores several factors, such as biodiversity, ocean acidification and sea level rise. Therefore, Nordhaus and Sztorc (2013) set the parameter values to $\psi_1 = 0.00267$ and $\psi_2 = 2$ to include additional damage equivalent to a further 25% of the extent of damage cited above as a representative estimate.

This extent of damage is supported by Anthoff and Tol (2010) and Hope (2011). The TFP, $A(t)$, and the population growth, $L(t)$, are exogenous. These quantities take the forms

$$\begin{aligned} A(t+1) &= A(t) [1 + g_A(t)], \\ L(t+1) &= L(t) [pop/L(t)]^{padj}, \end{aligned}$$

where $g_A(t) = 0.079 \cdot e^{-\delta_A \cdot t}$ and δ_A , pop , and $padj$ represent the rate of decline of the TFP, the future population, and the rate of population growth, respectively. The values of these three parameters are assumed to be 0.03, 10500, and 0.134, respectively. The gross output, $Q(t)$, is divided into a consumption term, $C(t)$, and an investment term, $I(t)$:

$$Q(t) = C(t) + I(t).$$

In this model, the per capita consumption is defined as

$$c(t) = \frac{C(t)}{L(t)}.$$

Finally, the capital stock, $K(t)$, is given by

$$K(t) = I(t) - \delta_K K(t-1),$$

where δ_K is the capital depreciation rate and has a value of 0.1.

2.2 Emission and carbon cycle constraints

The original DICE model considers the carbon cycle. Concretely, the carbon cycle as modelled in the original DICE model consists of three layers: the atmosphere, the upper ocean and the deep ocean. In addition, countries release CO_2 from production activities in every time period, and emissions based on land use are specified exogenously in every period.

These CO₂ emissions circulate through the three layers of the model.

A country's total emission $E(t)$ is given by

$$E(t) = E_{Ind}(t) + E_{Land}(t),$$

where $E_{Ind}(t)$ represents the emission from the country's production activities and $E_{Land}(t)$ represents its emissions related to land use. The corresponding equations are

$$\begin{aligned} E_{Ind}(t) &= \sigma(t) [1 - \mu(t)] A(t)K(t)^\gamma L(t)^{1-\gamma}, \\ E_{Land}(t) &= eland0 \times (1 - deland)^{t-1}, \end{aligned}$$

where $\sigma(t)$ is the level of carbon intensity, $eland0$ is the amount of CO₂ from land use released in 2010, and $deland$ is the rate of decline of land use emissions. Nordhaus and Sztorc (2013) assumed that $\sigma(t)$ is given by $\sigma(t+1) = \sigma(t) \cdot e^{g_\sigma(t)}$, with $g_\sigma(t+1) = 1.001 \cdot g_\sigma(t)$. $E_{Land}(t)$ is an exogenous value, and $eland0$ and $deland$ are assumed to be 3.3 and 0.2, respectively. The DICE model assumes three reservoirs of carbon: the amount of carbon in the atmosphere is denoted by $M_{AT}(t)$, that in the upper ocean is denoted by $M_{UP}(t)$, and that in the deep ocean is denoted by $M_{LO}(t)$. The equations describing the carbon cycle are as follows:

$$\begin{aligned} M_{AT}(t) &= E(t) + \phi_{11}M_{AT}(t-1) + \phi_{21}M_{UP}(t-1), \\ M_{UP}(t) &= \phi_{12}M_{AT}(t-1) + \phi_{22}M_{UP}(t-1) + \phi_{32}M_{LO}(t-1), \\ M_{LO}(t) &= \phi_{23}M_{UP}(t-1) + \phi_{33}M_{LO}(t-1). \end{aligned} \tag{6}$$

The coefficients ϕ_{ij} are parameters representing the flow from reservoir i to reservoir j ³. Nordhaus set these parameters as constants in his three-reservoir model. The accumulation of CO₂ causes global warming as a result of increases in radiative forcing. This model follows

³ $\phi_{11} = 0.912$, $\phi_{21} = 0.0383$, $\phi_{12} = 0.088$, $\phi_{22} = 0.9592$, $\phi_{32} = 0.0003375$, $\phi_{23} = 0.0025$, and $\phi_{33} = 0.9996625$.

the original DICE model:

$$F(t) = \eta \log_2 \frac{M_{AT}(t)}{M_{AT}(1750)} + F_{EX}(t),$$

where $F(t)$ is the change in the total radiative forcing caused by GHGs from anthropogenic sources, such as CO₂, since 1750. $F_{EX}(t)$ represents exogenous forcing ⁴, and η is an adjustable parameter that is assumed to have a value of 3.8. Moreover, the air temperature and the deep ocean temperature are defined as follows:

$$\begin{aligned} T_{AT}(t) &= T_{AT}(t-1) + \xi_1 \{F(t) - \xi_2 T_{AT}(t-1) - \xi_3 [T_{AT}(t-1) - T_{LO}(t-1)]\}, \\ T_{LO}(t) &= T_{LO}(t-1) + \xi_4 [T_{AT}(t-1) - T_{LO}(t-1)], \end{aligned}$$

where $\xi_1 = 0.098$, $\xi_2 = 1.31$, $\xi_3 = 0.088$, and $\xi_4 = 0.025$. These equations are explained in detail in the manual for the DICE model (Nordhaus and Sztorc, 2013). The main parameters are listed in the Appendix. For actual calculations using the DICE model, the time step is chosen to be 5 years, 60 time periods (300 years) are assumed, and the initial values are as shown in Table 1.

Table 1: Initial conditions

A(1)	L(1)	Q(1)	K(1)	$\mu(1)$	E(1)	$\sigma(1)$
	[mil.]	[\$tril.]	[\$tril.]		[GtCO ₂ /yr]	
3.8	6838	63.69	135	0.039	33.61	0.549

⁴ $F_{EX}(t)$ is assumed to obey the following equation: $F_{EX}(t) = \begin{cases} 0.025t + 0.25 & (t < 19) \\ 0.7 & (19 \leq t) \end{cases}$.

3 New backstop technology

We formulate a new model, the CEEM, by adding two new features to the DICE model: an additional kind of backstop technology and the ocean ecosystem. As discussed later, the addition of these features leads to crucial changes in the optimal solution and the evaluation of the 2-degree and 1.5-degree targets.

3.1 Modelling of two backstop technologies

The cost of a backstop technology in the DICE model is given as follows:

$$p(t) = pback(1 - gback)^{t-1}, \quad (7)$$

where $pback$ is the initial cost (\$/tCO₂) of the backstop technology and $gback$ is the rate of decline of this cost. $p(t)$ is a decreasing function, and the abatement cost ratio, $\Lambda(t)$, decreases as $p(t)$ decreases. Thus, the rate of emission reduction, $\mu(t)$, will readily increase as time goes on.

The costs for backstop technologies based on renewable energy, such as solar power, and other technologies will be lower in the future, but not all such technologies are safe for the environment. The impacts of CCS, for example, have not yet been sufficiently explored. Therefore, this study suggests the modelling of two kinds of backstop technologies: one is the type of technology supported by the DICE model, and the other is a technology that can exert undesirable effects on the environment. We refer to these types of technologies as conventional backstop technology (BT1) and CCS-type backstop technology (BT2). The corresponding costs, in analogy to Eq. (7), are given as follows:

$$p_1(t) = pback_1(1 - gback_1)^{t-1},$$
$$p_2(t) = pback_2(1 - gback_2)^{t-1}.$$

Let $x(t)$ be the rate of BT2 use; then, Eq. (4) becomes

$$\Lambda(t) = \theta_1(t) \{ [1 - x(t)]p_1(t) + x(t)p_2(t) \} \mu(t)^{\theta_2}.$$

Hence, the emission reduction achieved by means of BT2, $E_{BT2}(t)$, is given by

$$E_{BT2}(t) = \sigma(t)\mu(t)x(t)A(t)K(t)^\gamma L(t)^{1-\gamma}.$$

A BT2 technology, such as CCS, carries a risk of CO₂ leakage into the ocean or the atmosphere, which may cause an increase not only in temperature but also in ocean acidification. To analyse the impact of this risk, we define $V(t)$ as the amount of BT2 storage in time period t :

$$V(t+1) = [1 - l(t)]V(t) + E_{BT2}(t),$$

where $l(t)$ is the leakage rate in period t and is specified exogenously. Then, for example, when we assume that the leakage occurs into the atmosphere and upper ocean, Eq. (6) becomes

$$\begin{aligned} M_{AT}(t) &= E(t) + \phi_{11}M_{AT}(t-1) + \phi_{21}M_{UP}(t-1) + k \cdot l(t)V(t), \\ M_{UP}(t) &= \phi_{12}M_{AT}(t-1) + \phi_{22}M_{UP}(t-1) + \phi_{32}M_{LO}(t-1) + (1-k)l(t)V(t), \\ M_{LO}(t) &= \phi_{23}M_{UP}(t-1) + \phi_{33}M_{LO}(t-1), \end{aligned} \quad (8)$$

where k is the rate of leakage into the atmosphere. It can be interpreted as being determined by the ratio of on-shore storage to off-shore storage, which is not explicitly modelled.

3.2 Backstop technologies and the optimal strategy

In this section, we demonstrate the effects of varying the rate and sites of leakage on the optimal solution. We compute the optimal solution under three different assumptions regarding the leakage rate $l(t)$: (i) the leakage is constant over time, $l(t) = 0.02$; (ii) the leakage is increasing at a low rate, $l(t) = 0.01 \cdot 1.01^{t-1} - 0.01$; and (iii) the leakage is increasing at a high rate, $l(t) = 0.01 \cdot 1.05^{t-1} - 0.01$. As mentioned by Widdicombe et al. (2013), the risk of leakage is a matter of concern. The leakage itself is uncertain, and the level of risk is not well known. Hence, to be conservative, we assume that the leakage is certain and investigate whether BT2 should be used or not under this assumption.

First, we consider the case of leakage only into the upper ocean, namely, $k = 0$ in Eq. (8). The initial cost of BT1, $pback_1$, is chosen to be 344 (\$/tCO₂), the same as in the DICE model, version 2013R. As discussed above, BT2 is assumed to be an inferior type of technology compared with BT1 because BT2 involves leakage. Therefore, if BT2 is more expensive than BT1, BT2 will never be used at all. Accordingly, we set the initial cost of BT2 to 300, which is lower than that of BT1; this particular value is chosen for convenience. Table 2 summarizes the parameters related to the backstop technologies.

Table 2: Parameters related to backstop technologies

parameter	
$p_i(t)$	the cost of backstop technology i in time period t ($i = 1, 2$)
$pback_i$	the initial cost of backstop technology i ($i = 1, 2$)
$gback_i$	the rate of decline of the cost of backstop technology i ($i = 1, 2$)
$l(t)$	the leakage rate in time period t
k	the leakage rate into the atmosphere
variable	
$x(t)$	the rate of BT2 use

Figure 1 and Figure 2 illustrate the carbon emissions and the emission control rates, respectively, under the various leakage conditions. The solid lines represent the original DICE model, and the other lines correspond to cases in which BT2 is considered with

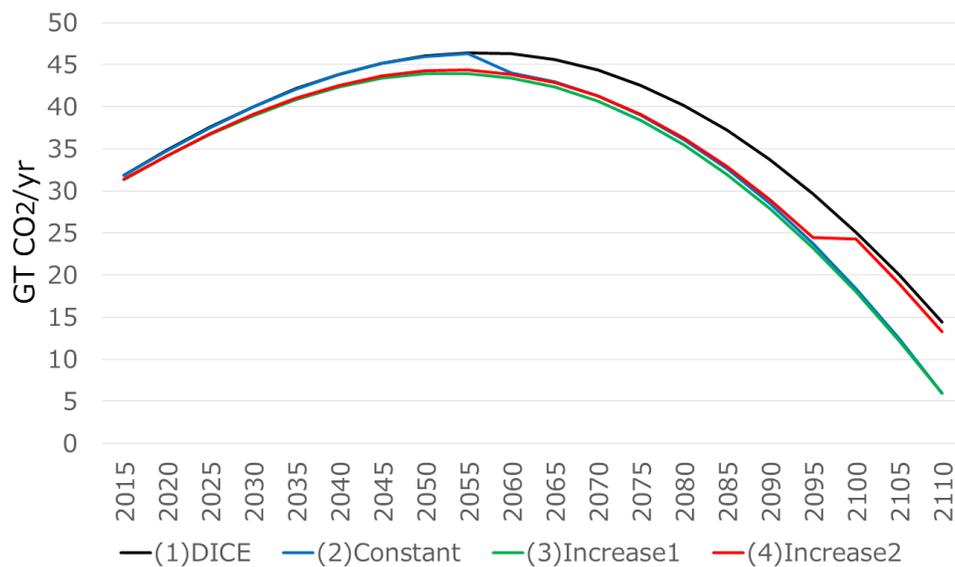


Figure 1: Total carbon emission

Note: (1) Original DICE model. (2) Constant leakage: $l(t) = 0.02$. (3) Increasing leakage: $l(t) = 0.01 \cdot 1.01^{t-1} - 0.01$. (4) Increasing leakage: $l(t) = 0.01 \cdot 1.05^{t-1} - 0.01$.

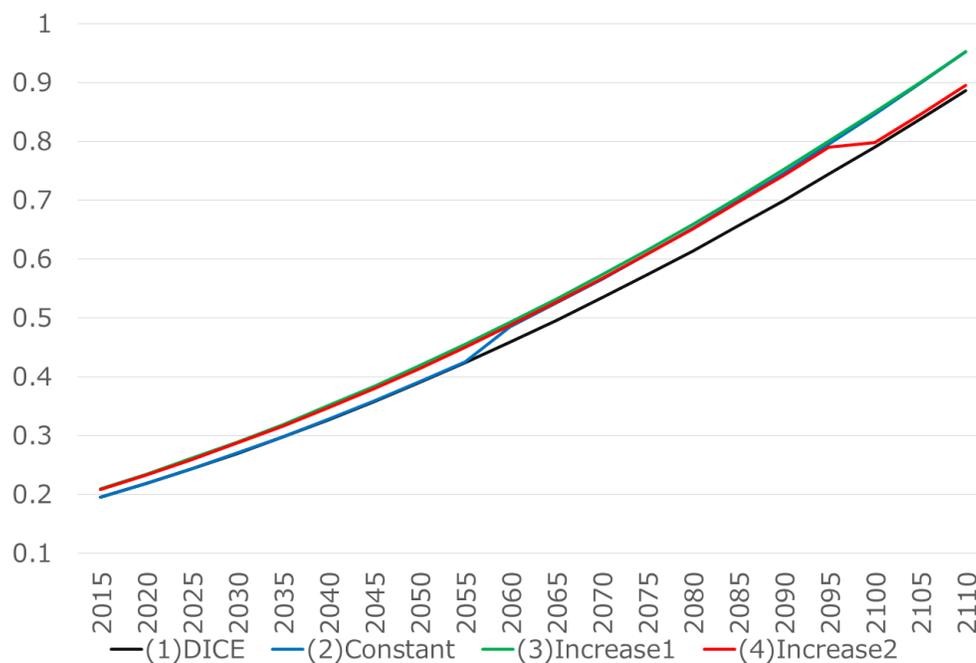


Figure 2: Emission control rate

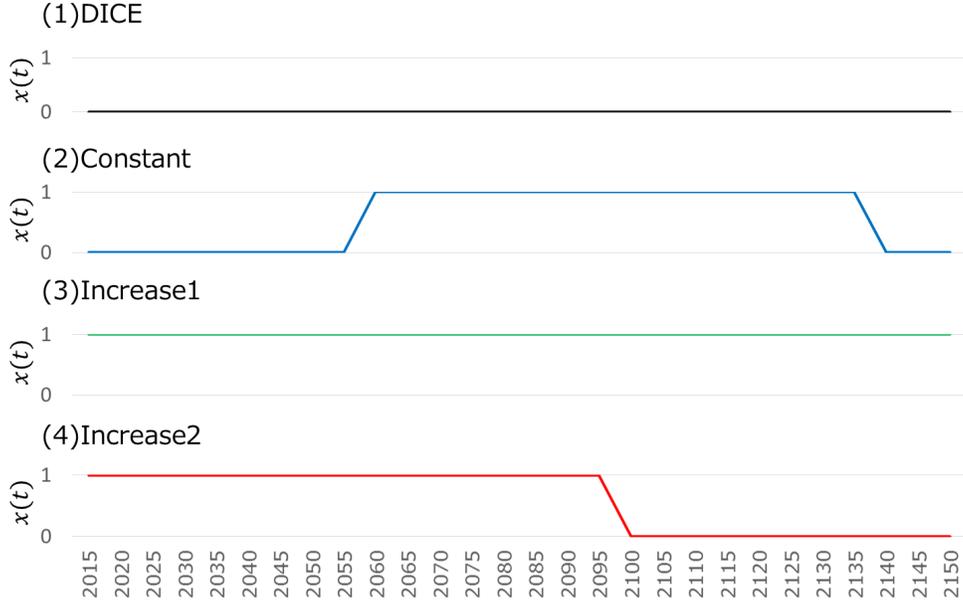


Figure 3: Backstop technology utilization

different leakage rates. By comparing the DICE model with the other settings, we can see that emissions are reduced when BT2 is available. The dashed lines, which represent the three settings with BT2, show different patterns of both the total carbon emission and the emission control rate. To elucidate the mechanism behind these patterns, let us consider Figure 3, which illustrates the utilization of the backstop technologies. We find that differences in the relative rates of use of these technologies arise from the different leakage conditions, and the levels of emission differ considerably depending on the situation. In particular, we note that the timings of the introduction and discontinuation of the different technologies change depending on the leakage situation. For example, if the leakage rate is constant (e.g., $l(t) = 0.02$), then we should not introduce BT2 until approximately 2060 and should stop using BT2 in approximately 2140. By contrast, if the leakage rate is exponentially increasing (e.g., $l(t) = 0.01 \cdot 1.05^{t-1} - 0.01$), then we would be better served to introduce BT2 as soon as possible. Note that the utilization differs depending on the initial cost, the leakage rate, the cost decline rate, and other parameters.

Moreover, the utilization of the different backstop technologies differs depending on the

leakage sites. In the above analysis, we assume that leakage occurs only into the upper ocean, but there is a possibility that leakage may occur not only into the ocean but also near the ground. This would further accelerate the elevation of the atmospheric temperature. Figure 4 illustrates the utilization situation of the backstop technologies in the case of $k = 0.2$. The other parameters are the same as in the above analysis. By comparing the different possible leakage locations, we can see that BT2 is difficult to use at all in the case of leakage into the atmosphere and ocean; a comparison of Figure 3 and Figure 4 shows that when the leakage rate is $l(t) = 0.2$ or $l(t) = 0.01 \cdot 1.05^{t-1} - 0.01$, BT2 falls out of favour compared with the case of $k = 0$. For the leakage case corresponding to $l(t) = 0.01 \cdot 1.01^{t-1} - 0.01$, the utilization does not change with variations in the parameter k . The reason for this must be that the absolute amount of leakage in the case of $l(t) = 0.01 \cdot 1.01^{t-1} - 0.01$ is smaller than in the other cases.

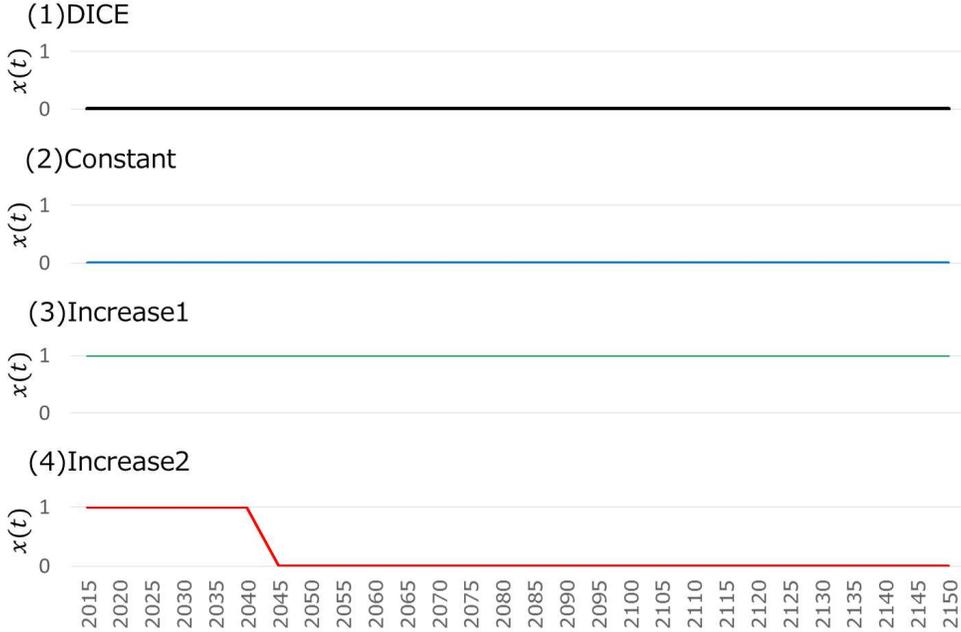


Figure 4: Backstop technology utilization for $k = 0.2$

From these results, we can see that introducing new technologies is of great worth even if these technologies carry leakage risks. Technologies such as BT2 will be useful in the case

of low leakage into the atmosphere. However, we should note that leakage into the ocean will cause acidification and may damage the ocean ecosystem.

4 Ocean ecosystem

4.1 Framework for including ecosystem damage

Next, we consider the impact on the ocean ecosystem. The leakage of CO_2 from storage areas may cause not only an increase in temperature but also environmental damage, such as ocean acidification. This acidification will exert undesirable effects on the ocean ecosystem, e.g., inhibition of the growth of shellfish.

The ocean ecosystem provides several kinds of services (Barbier et al., 2011). Damage to the ocean ecosystem caused by acidification will eventually cause damage to the economy. As described above (section 2.1), the damage function given in Eq. (5) already considers the economic damage to the ocean ecosystem. However, there are expected to be additional factors that would be difficult to convert into economic costs. Based on their survey, Adams and Adger (2013) suggested that the well-being of the ecosystem is of considerable importance. Although, in general, many researchers use consumption as the only variable in the utility function, there is some disagreement regarding this approach. Jones and Klenow (2016) suggested that the utility function should include not only consumption but also leisure, mortality, and inequality, whereas Grimaud and Rouge (2008) defined the utility as a function of consumption and environment stock in their model. Hence, we use the utility function defined as follows.

This study demonstrates the effect of introducing an acidification index, such as pH , into the model to consider its impact. Let $Z(t)$ (mol/l) denote the concentration of carbonic acid

gas in the upper ocean; then, the pH is given by

$$\begin{aligned} pH(t) &= \frac{pK - \log Z(t)}{2}, \\ Z(t) &= \frac{M_{UP}(t)}{\zeta}, \end{aligned}$$

where pK is the dissociation constant and ζ is an adjustment parameter. Then, we assume that damage to the ecosystem results in a decrease in utility. Let $G(t)$ be the decrease in utility caused by a change to the level of ocean acidification; then,

$$G(t) = [pH(t) - pH(0)]^2, \quad (9)$$

under the assumption that the economic loss due to a deviation of the pH from its initial level grows quadratically. Consequently, Eq. (1) becomes

$$\sum_{t=1}^T \{U[c(t), L(t)] - \omega G(t)\} (1 + \rho)^{-t}, \quad (10)$$

where ω is a damage parameter. Note that these functional forms and parameters are not supported by quantitative empirical evidence. Consequently, the outcomes of the model should not be treated as quantitatively accurate, only qualitatively.

4.2 Results of the CEEM

First, the acidification parameters are set as follows. Although measurements of pH in the ocean are not straightforward, the pH values typically range from 7.7 to 8.2 (Brewer et al., 1995). Based on these values, we assume that the initial pH value $pH(0)$, pK and ζ are 8.21, 6.5 and 2.42×10^7 , respectively. With these values, in the original DICE model, the pH value becomes 8 or 7.9 when the atmospheric temperature increases by approximately 2.3 degrees or 3.3 degrees, respectively. These predictions are not inconsistent with estimations from other researchers, such as Haugan and Drange (1996) and Caldeira and Wickett, who

have noted the possibility of a reduction in pH by 0.2 - 0.5 units over the next century.

The degree of ocean acidification is directly affected by the amount of carbon in the upper ocean, M_{UP} , in this model. Depending on whether leakage occurs only into the ocean ($k = 0$) or into both the atmosphere and the ocean ($k > 0$), the resulting level of acidification differs. Figure 5 shows the backstop technology utilization $x(t)$ for the leakage scenario characterized by $l(t) = 0.01 \cdot 1.05^{t-1} - 0.01$ for four pairs of values of the parameter representing the utility loss caused by acidification, ω , and the parameter representing the rate of leakage into the atmosphere, k : $(\omega, k) = (0, 0)$, $(0, 0.2)$, $(10, 0)$ and $(10, 0.2)$. First, let us compare the first two cases, $(\omega, k) = (0, 0)$ and $(\omega, k) = (0, 0.2)$. We find that BT2 is used less often in the case of leakage into both the atmosphere and the ocean ($k = 0.2$) compared with leakage into only the ocean ($k = 0$). This trend does not change even when acidification is considered to cause a decrease in utility ($\omega = 10$). The effect of a change in the damage parameter is quite intuitive. A comparison between the two cases with $\omega = 0$ and the two cases with $\omega = 10$ shows that the decrease in utility caused by acidification results in a decrease in BT2 utilization. In other words, when the value of the damage parameter ω is higher, CO_2 leakage is more undesirable.

Let us explore the effect of the damage parameter ω in greater detail. Figure 6 shows the results of optimal control for four levels of the damage parameter ω : 0, 10, 30, and 100. The parameter describing the leakage into the atmosphere, k , is set equal to 0 in this exercise. A higher level of the parameter ω leads to higher emission control rates, as depicted in Figure 6-(C). Because of the change in the emission control rate, industrial emissions are reduced, and the elevation of the temperature of the atmosphere is also suppressed. In the case of $\omega = 100$, the atmospheric temperature in 2100 is 0.5 degrees lower than in the case of $\omega = 0$, and the social cost of carbon is approximately two times higher than in the case of $\omega = 0$.

In both the DICE model and the CEEM, we maximize the total utility (see Eq. (1) and Eq. (10)). The introduction of the parameter ω represents the reduction in the total utility caused by acidification. Table 3 shows the resulting utility increase (or decrease). We regard

the utility in 2010 as the reference point and set it equal to 0. As the value of ω increases, the disutility due to acidification also increases. Note that the disutility due to acidification is less than 1% of the consumption utility in this analysis. In addition, the consumption utility decreases as ω increases. It appears that the reason for this relationship is the increase in the emission control rate. Although the increase in the emission control rate has a suppressing effect on the consumption utility, the disutility due to acidification is also suppressed. A key observation is that although the direct effect on the total utility caused by acidification is not large, it can cause a material change in the optimal strategy.

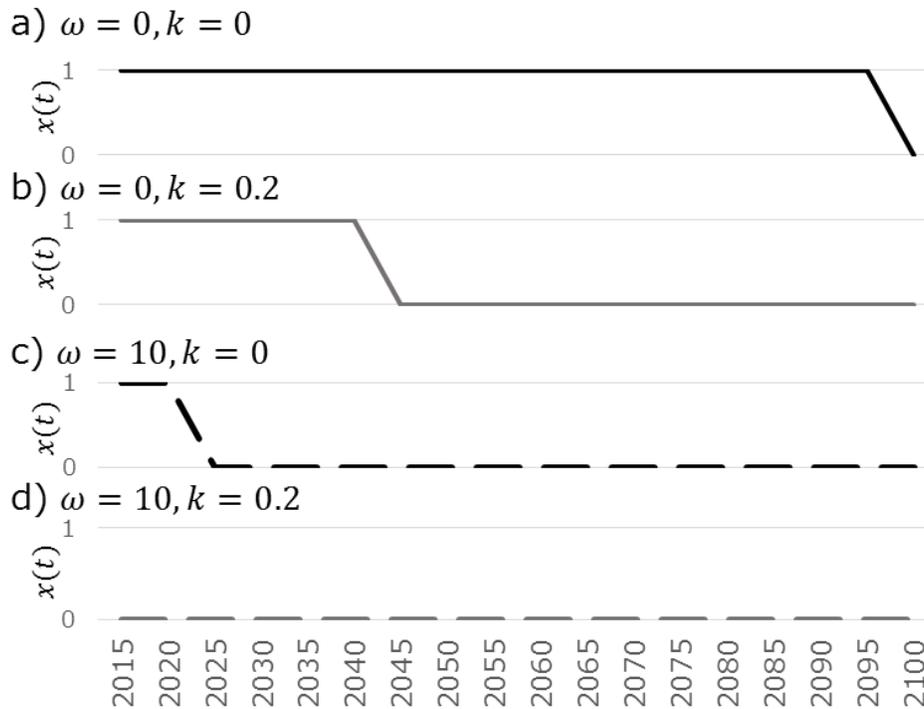


Figure 5: Backstop technology utilization considering ocean acidification

Note: The value of the damage parameter ω is 0 for (a) and (b) and 10 for (c) and (d). Moreover, (a) and (c) correspond to leakage only into the ocean, whereas (b) and (d) represent cases in which 20% of the leakage goes into the atmosphere.

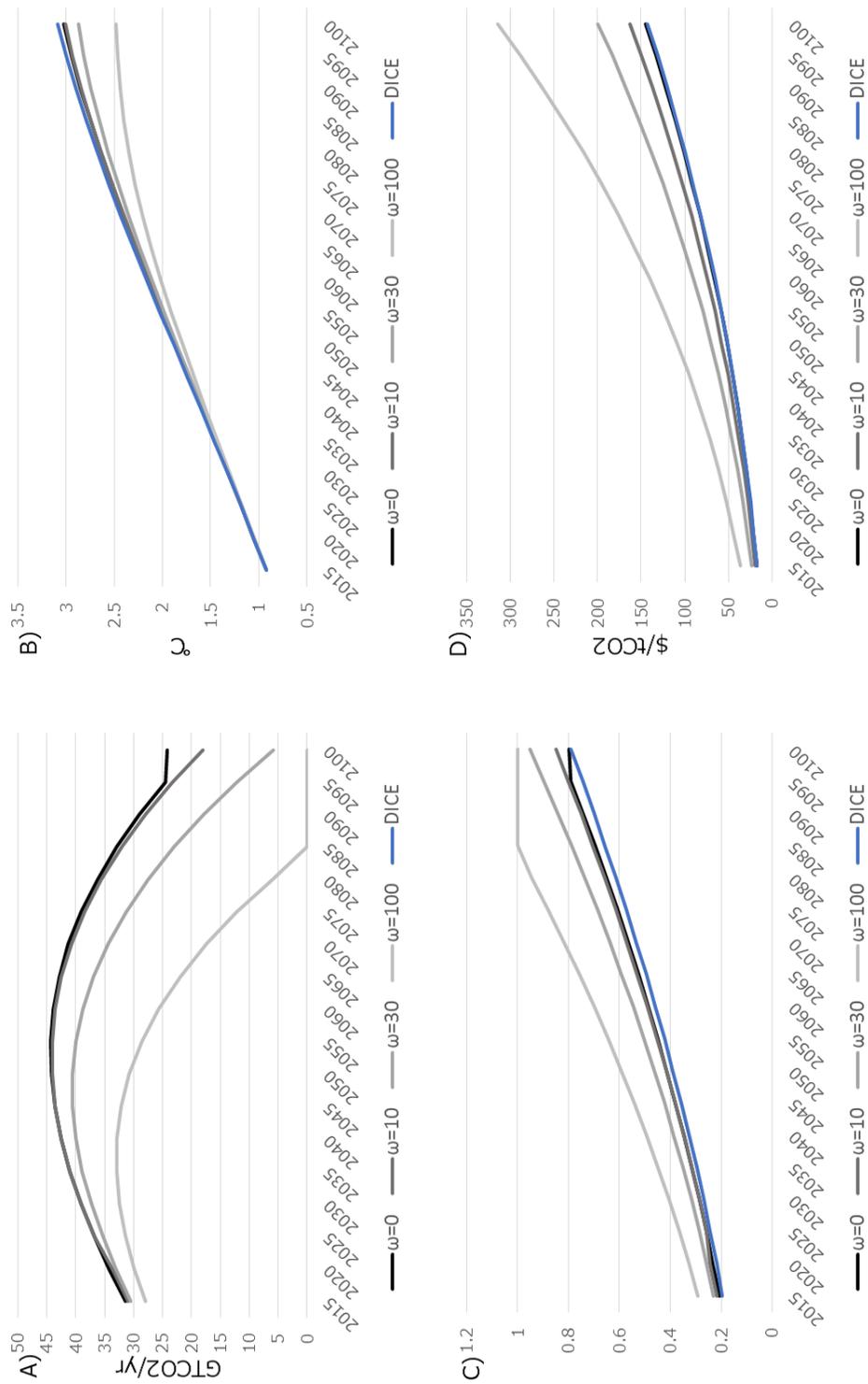


Figure 6: Optimal control for various values of the damage parameter ω

Note: (A), (B), (C), and (D) present industrial emissions (GTCO₂/year), the atmospheric temperature (°C above preindustrial), the emission control rate, and the social cost of carbon, respectively.

Table 3: Changes in utility with variations in the parameter ω

	Utility	2015	2020	2030	2050	2070	2090
$\omega = 0$	Consumption	39.3	78.4	153.6	284.6	386.1	462.2
	Acidification	0	0	0	0	0	0
$\omega = 10$	Consumption	39.2	78.3	153.5	284.4	385.8	461.8
	Acidification	0	0	-0.1	-0.2	-0.3	-0.5
$\omega = 30$	Consumption	39.1	78.1	153.2	283.9	385.2	461.2
	Acidification	0	-0.1	-0.2	-0.5	-0.9	-1.3
$\omega = 100$	Consumption	38.8	77.5	152.3	282.4	383.2	460
	Acidification	-0.1	-0.3	-0.6	-1.5	-2.6	-3.7

Note: These utility values represent the increase (or decrease) with respect to the utility in 2010. The consumption utility and the acidification utility correspond to $U(\cdot)$ and $\omega G(t)$, respectively.

4.3 2-degree target and 1.5-degree target

Here, let us consider a 2-degree target and a 1.5-degree target. A 2-degree target was adopted in the Copenhagen Accord, and this target has been referenced at various international conferences. Moreover, a stricter 1.5-degree target has become a focus since COP21. Nordhaus (2014) estimated the social cost of carbon (SCC) in the context of the 2-degree target using the DICE model, version 2013R, and found that the SCC rises sharply.

In this section, we compare the results of the DICE model and the CEEM model when evaluating the 2-degree target and the 1.5-degree target. We assume that the leakage is characterized by $l(t) = 0.01 \cdot 1.05^{t-1} - 0.01$ and $k = 0$. For the damage parameter ω , we use three values: 0, 30, and 100. Table 4 shows the estimated SCC values. In the case of the DICE model, the SCC values for the 2-degree case are 47.6, 216.4 and 561.8 (\$/tCO₂) in 2015, 2050 and 2090, respectively. These are approximately 2.6, 4.1 and 4.7 times the SCC values for the baseline case. In the case of the CEEM with $\omega = 0$, meanwhile, the SCC values for the 2-degree case are 43.9, 199.2 and 790.4 (\$/tCO₂) in 2015, 2050 and 2090, respectively. These are approximately 2.4, 3.7 and 6.6 times the SCC values for the baseline case. The SCCs obtained using the CEEM are lower than those from the DICE model in the near future, but they sharply increase and become larger than those from the DICE

model in the far future. This behaviour seems to be due to the influence of BT2. BT2 can store CO₂, but the stored CO₂ is assumed to gradually leak in this model. This means that current emissions are suppressed at the cost of increased emissions in the far future. Hence, we can achieve a lower SCC in the near future, but the problem will come back to haunt us in the far future.

Next, we focus on the case of the 1.5-degree target. We find that the SCC increases considerably compared with the SCC values in the cases of the baseline, the optimal control strategy, and the 2-degree target, as shown in Table 4. The values for the 1.5-degree case are more than 10 times those for the baseline case. Figure 7 presents the ratio of the SCC values between the DICE and CEEM evaluations. This ratio increases more slowly under the 1.5-degree target than it does under the 2-degree target. For example, the SCC in 2100 that is indicated by the CEEM with $\omega = 30$ is 1.4 times that indicated by the DICE model in the case of the 1.5-degree target, whereas it is 2.2 times that indicated by the DICE model in the case of the 2-degree target. By contrast, between 2050 and 2080, the ratio is approximately 1 in both cases, although the ratio for the 2-degree case is slightly lower than that for the 1.5-degree case until approximately 2075. Furthermore, the ratio approaches 1 as the parameter ω increases. As shown in Figure 8, BS2 is also increasingly rarely used as the parameter ω increases. From these results, we find that the use of BT2 postpones the impact of climate change. In addition, for $\omega = 100$, BT2 is used only until 2035 in the case of the 1.5-degree target and is not used at all in the case of the 2-degree target. Consequently, the difference between the DICE and CEEM results is relatively small.

Figure 9 illustrates the change in the emission control rate. The rates for the 2-degree target and the 1.5-degree target are little affected by increasing ω , unlike in the optimal control case. The rate reaches 1 in either 2060 or 2030 for the case of the 2-degree target or the 1.5-degree target, respectively, regardless of any increase in ω . That is, under both targets, an enormous amount of CO₂ emissions must be processed using backstop technologies in the near future. In particular, in the case of the 1.5-degree target, we will need to begin

eliminating the majority of emissions within the next few years. In addition, in the case of the adoption of a strict target, the index representing the level of ocean acidification as expressed in Eq. (9) takes on a smaller value compared with the other cases. Namely, the decrease in utility caused by acidification, $\omega G(t)$ (in Eq. (10)), is not as large as in the cases of the other, less strict targets. Consequently, the influence of increasing ω is reduced as the target becomes more strict. The cost of a backstop technology is defined as a decreasing function over time, such that using BS2 earlier results in a larger benefit than using it later. In the case of the 1.5-degree target, the benefit of using BT2 exceeds the cost of the leakage because of the enormous amount of emissions that must be eliminated. As a result, BT2 is used only during a short period of the early stage regardless of the value of ω . By contrast, in the case of the 2-degree target, because the required emission reduction is not as large as in the case of the 1.5-degree target, the usage of BT2 does depend on ω , as shown in Figure 8.

Our work assesses the potential of CCS as a mitigation technology at the global level, based on previous experimental studies. From our results, we can say that if we hope to achieve a strict target (such as 1.5-degree target), technologies that reduce CO₂ emissions but carry a risk of ecosystem damage may be useful for reaching that target. In particular, in this model, we assume that these new technologies are certain to result in the leakage of CO₂. Therefore, these new technologies should be used to a greater extent if the actual probability of leakage is low. In addition, note that the optimal use of these new technologies will change with the magnitude of the utility from the ecosystem, but in the case of the adoption of a strict target, we may be more willing to accept the utility decrease due to ecosystem damage. Ecosystem damage will already be reduced by achieving such a strict target, so there is a possibility that the damage caused by using new, risk-bearing technologies may be negligible.

Table 4: Social costs of carbon under the DICE model and the CEEM ($\$/tCO_2$)

Scenario	2015	2020	2030	2050	2070	2090
DICE						
Baseline	18.6	22.1	30.6	53.2	83.1	119.8
Optimal control	17.7	21.2	29.3	51.5	81.9	120.6
2-degree target	47.6	60.1	94.4	216.4	437.2	561.8
1.5-degree target	196.2	249.3	406.4	1080.5	2576.3	4833.1
CEEM $\omega = 0$						
Optimal control	17.7	21.2	29.4	51.7	82.7	122.3
2-degree target	43.9	55.2	86.3	199.2	431.5	790.4
1.5-degree target	194.7	247.1	402.2	1072.1	2668.9	5824
CEEM $\omega = 30$						
Optimal control	23.7	28.3	39.4	70.1	112.9	167.8
2-degree target	46.2	57.7	88.7	197.2	396.8	592
1.5-degree target	194.8	246.9	400.5	1061	2617.9	5605.6
CEEM $\omega = 100$						
Optimal control	36.9	44	61.3	109.3	176.2	263.1
2-degree target	54.8	67.3	100.1	207.6	387.7	503.7
1.5-degree target	193.5	244	391.3	1020.2	2472.4	5137.6

* “Optimal control” is the scenario in which there is no temperature target.

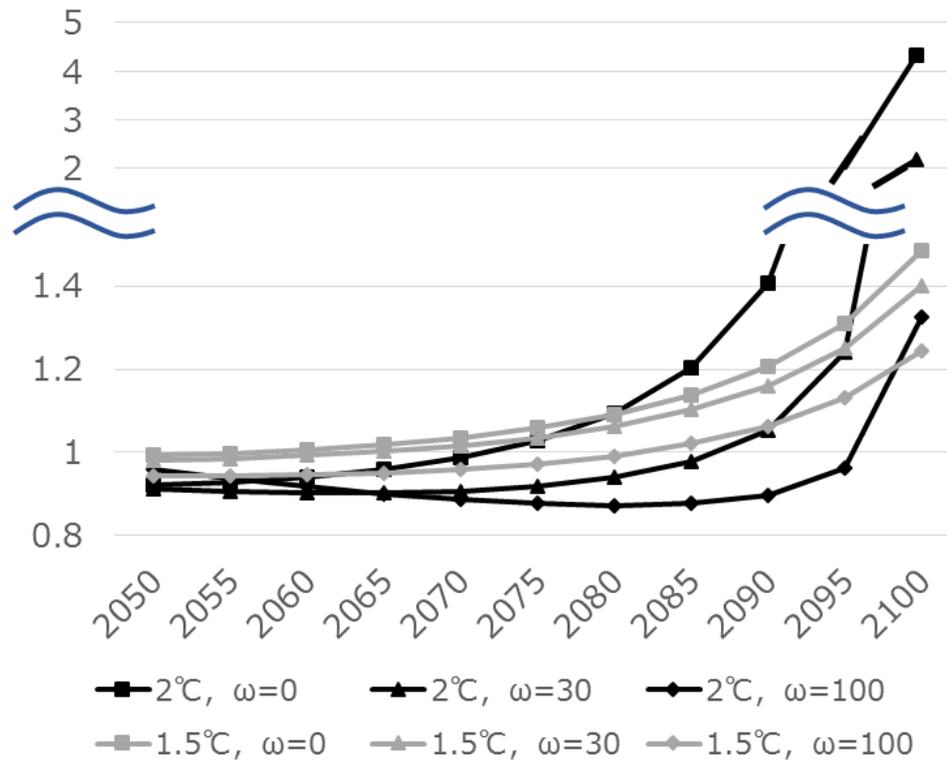


Figure 7: Ratio of the SCC values between the DICE model and the CEEM

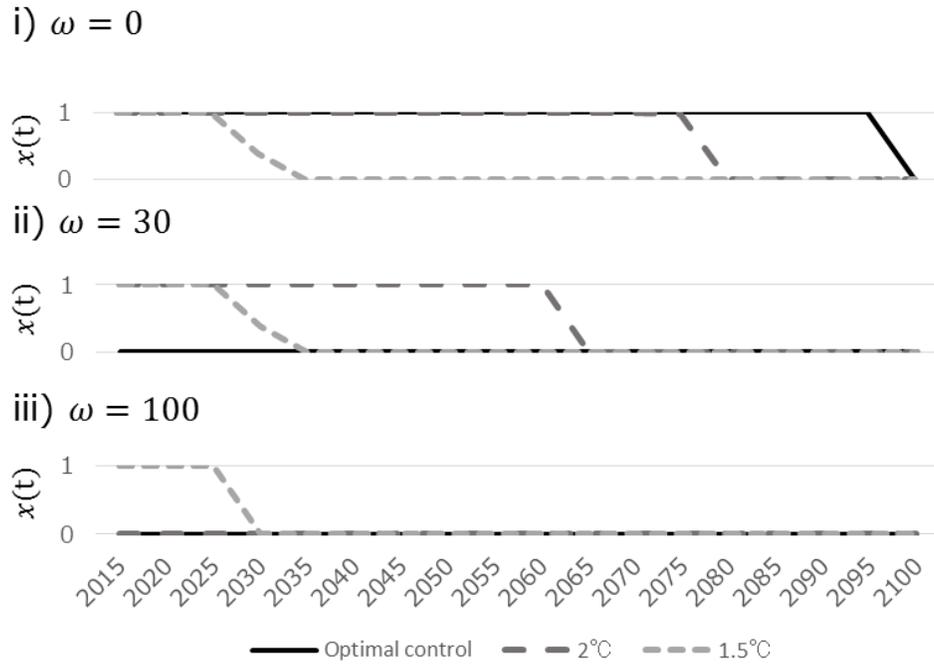


Figure 8: Backstop technology utilization for various values of the parameter ω

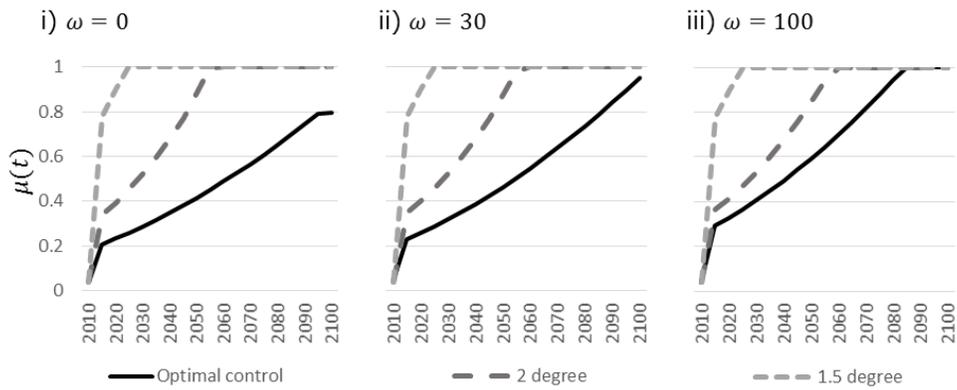


Figure 9: Emission control rates for various values of the parameter ω

5 Conclusion

This paper examines the role of CCS technologies in combating climate change. In particular, we attempt to judge whether new technologies that offer reasonable CO₂ control but carry a risk of ecosystem damage should be used under the 2- and 1.5-degree targets. Although the CCS-type technologies that we model can capture CO₂ and delay climate change, they are known to present the possibility of leakage and harmful effects on the ecosystem. To capture this trade-off, we established an evaluation framework that considers two types of backstop technologies (BT1 and BT2) and the ocean ecosystem. Using this framework, we explored the optimal solution and other policy plans, such as 2- and 1.5-degree targets.

First, we explored the optimal use of BT2 in a simple setting without any harmful effects of BT2 on ocean acidification. We found two intuitive tendencies: (i) when the leakage rate is lower, BT2 is used more extensively, and (ii) when more leakage goes into the atmosphere, BT2 is used less extensively. The second relationship holds because leakage into the atmosphere causes the atmospheric temperature to increase more quickly than leakage into the ocean does. Interestingly, we also observed that a delay in beginning the use of BT2 is sometimes optimal.

Next, in a setting in which the harmful effects of BT2 on the ocean ecosystem are considered, we examined the optimal use of BT2 for various values of the parameter that determines the economic cost of acidification, ω . Here, we found that when acidification is regarded as more costly, BT2 is used to a lesser extent because the leakage becomes more costly and overshadows the benefit of the low implementation cost. Depending on the value of ω , the resulting increase in the atmospheric temperature by the end of this century was found to vary from 2.5 to 3 degrees, with the impact on the utility level remaining below 1%.

Under the 2- and 1.5-degree targets, we found a different pattern. In contrast to the case of the optimal solution (with no temperature target), varying the economic cost of acidification, ω , does not strongly impact the optimal plan under the 2- or 1.5-degree target. There appear to be two reasons for this finding. One is that in the case of the 2- or 1.5-degree

target, an enormous amount of emissions must be eliminated early on, and consequently, the cost advantage of BT2 is valued more highly. The other is that if we adopt a strict target, the index representing the level of ocean acidification ($G(t)$) becomes smaller than in the case of a laxer target. As a result, the term expressing the decrease in utility caused by acidification, $\omega G(t)$, does not become as large with increasing ω as it does for laxer targets. In the case of the largest considered ω value, BT2 is used only in the case of the 1.5-degree target. In the optimal solution, BT1 is always employed, and BT2 is never used. This observation tells us that if we adopt a target temperature that is too tight, we might end up employing a technology that sacrifices the ecosystem too greatly.

Finally, we considered the SCC. The SCC in the case of the 2-degree target is much higher than that in the optimal control case, and the SCC in the case of the 1.5-degree target is even higher than that under the 2-degree target. The difference between the DICE and CEEM evaluations becomes increasingly large in the far future because of the use of BT2. We found that by using BT2, we can keep the SCC at a lower value in the near future, but this comes at the cost of a greater increase in the far future. However, the difference between the DICE model and the CEEM becomes small as the value of the parameter ω increases. This is because BS2 is rarely used at higher values of ω because of the enormous cost of acidification.

Nomenclature

Abbreviations

<i>BECCS</i>	bio-energy with CO ₂ capture and storage
<i>BT1</i>	conventional backstop technology
<i>BT2</i>	CCS-type backstop technology
<i>CCS</i>	CO ₂ capture and storage
<i>COP21</i>	2015 United Nations Climate Change Conference
<i>GHGs</i>	greenhouse gases
<i>IPCC</i>	Intergovernmental Panel on Climate Change
<i>SCC</i>	social cost of carbon
<i>TFP</i>	total factor productivity
<i>UNCED</i>	United Nations Conference on Environment and Development
<i>UNFCCC</i>	United Nations Framework Convention on Climate Change
<i>Models</i>	
<i>AD – DICE</i>	adaptation in DICE
<i>CEEM</i>	dynamic integrated climate-ecosystem-economy model
<i>DICE</i>	dynamic integrated climate-economy
<i>ENTICE</i>	endogenous technological change in DICE
<i>IAMs</i>	integrated assessment models

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Appendix

Table 5: Parameters of the DICE model

Parameter		Value
ρ	the discount rate	0.3
α	the elasticity of intertemporal substitution	1.45
γ	the elasticity of output	0.3
θ_2	adjustable parameter	2.8
ψ_1	parameter of the damage function	0.00267
ψ_2	parameter of the damage function	2
δ_k	the capital depreciation rate	0.1
ϕ_{11}	parameter representing CO ₂ flow	0.912
ϕ_{21}	parameter representing CO ₂ flow	0.0383
ϕ_{12}	parameter representing CO ₂ flow	0.088
ϕ_{22}	parameter representing CO ₂ flow	0.9592
ϕ_{32}	parameter representing CO ₂ flow	0.0003375
ϕ_{23}	parameter representing CO ₂ flow	0.0025
ϕ_{33}	parameter representing CO ₂ flow	0.9996625
η	adjustable parameter	3.8
ζ_1	adjustable parameter	0.098
ζ_2	adjustable parameter	1.31
ζ_3	adjustable parameter	0.088
ζ_4	adjustable parameter	0.025