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The permafrost carbon feedback in DICE-2013R modeling and empirical results

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Abstract Climate feedback mechanisms that have the potential to intensify global warming have been omitted almost completely in the integrated assessment of climate change and the economy so far. In the present paper, we incorporate the permafrost carbon feedback (PCF) into the well-known integrated assessment model DICE-2013R. We calibrate the parameters for our extended version of DICE-2013R and compute the optimal emission mitigation rates that maximize welfare. Our results indicate that accounting for the PCF leads to an increase in mitigation. Finally, we quantify the economic losses resulting from a climate policy which ignores the impacts of the PCF.

Keywords Integrated assessment · DICE model · Climate feedbacks · Permafrost

JEL Classification O44 · Q54 · Q58

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1 Introduction

Although the direct effects of greenhouse gases on global temperature are relatively well understood, estimation of the overall effects is complicated due to the existence of feedback mechanisms in the climate system. These mechanisms have the potential to accelerate global warming due to their self-enforcing character (e.g., Wolff et al. 2015).[1] The most important feedback mechanisms in the climate system are:

- *Snow and ice albedo feedback* Albedo is the fraction of the incoming solar radiation which is reflected from the earth back into space. Hence, the lower the albedo, the higher is the atmospheric temperature. Snow and ice have a high albedo, whereas water and land surface uncovered by snow or ice have a much lower albedo. Consequently, as snow and ice melts due to increasing temperatures, more of the sun's energy is absorbed. This leads to a further warming which in turn melts even more snow and ice implying a further decrease in albedo and further rising temperatures (IPCC 2013).
- *Ocean carbon sink feedback* Oceans absorb huge amounts of carbon dioxide depending on the atmospheric CO_2 concentration, the water temperature and biological processes triggered by plankton. As global warming can affect all parts of the atmospheric-ocean carbon exchange chain, long-term projections are difficult. However, it is obvious that an increase in water temperatures reduces the oceans' uptake capacity (Arora et al. 2013; Heinze et al. 2015). Consequently, with increasing temperatures a larger share of CO_2 emissions remains in the atmosphere leading to a further warming.
- *Permafrost carbon feedback* Permafrost is permanently frozen soil which often contains large amounts of organic carbon. When the soil thaws due to rising temperatures, the carbon content will become unlocked and be released to the atmosphere as CO_2 or CH_4. These additional emissions lead to further increasing temperatures and a further thawing of permafrost soils (see Sect. 2 for more details).

Evaluating the economic consequences of climate feedback mechanisms is a relatively new challenge. So far, these mechanisms have been omitted almost completely in the integrated assessment of climate change and the economy.[2] In the present paper we focus on the permafrost carbon feedback (PCF) which is one of the most studied and best understood climate feedback mechanisms. We show how to incorporate the PCF into the mathematical setup of the well-known integrated assessment model DICE-2013R (see Nordhaus 2013) and derive some empirical results.[3]

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[1] Additionally, there also exist some so-called negative feedback mechanisms that can slow down global warming (see, e.g., Wolff et al. 2015).

[2] The only exception is a short paper recently published by Gonzáles-Eguino and Neumann (2016) which, however, is more limited in scope than our analysis—see also Sect. 3.

[3] For readers not familiar with the DICE-2013R model we provide a short description in the Appendix.

Integrated assessment models (IAMs) are a popular tool when studying the economics of climate change (e.g., Hof et al. 2012). The major components of those IAMs are a neoclassical growth model and a climate module that is linked to the economic model. Important characteristics of those IAMs are their intertemporal formulation and the incorporation of a long time horizon. Since greenhouse gases have a long residence time in the atmosphere (often more than 100 years), this model setup is necessary for a meaningful assessment of climate change. Taking into account the mitigation costs and potential climate damage costs, one major subject of study in IAMs is the economically optimal emission mitigation path. Although we are aware of massive reservations against these models, we do not agree with the part of criticism that climatic feedback loops are "largely unknown" (Pindyck 2013, p. 870). On the contrary, we try to improve the model results by integrating the PCF to slightly reduce the simplifications of DICE-2013R.

The use of DICE-2013R for this paper has several reasons. Since the development of the first version of DICE (Nordhaus 1994), it is probably the most popular IAM in the economics of climate change and its codes are publicly available.[4] Due to its popularity, DICE entails the advantage that our results are comparable with those of many other studies using the same model family. This is particularly important since climatic feedbacks are closely related to tipping points[5] and potential catastrophes which have been assessed in a couple of studies within the DICE framework. For example, Mastrandrea et al. (2001) and Keller et al. (2004) show that optimal emission mitigation increases when uncertainty and potential catastrophes are included in the DICE-94 model. Ackerman et al. (2010) present a similar analysis for DICE-07, and Rezai (2010) introduces an upper limit for the atmospheric carbon absorption to account for potential catastrophes. Moreover, Lemoine and Traeger (2014) use DICE-07 to analyze the impact of multiple tipping points that reinforce each other's economic impacts.

The paper is organized as follows. In the next section, we describe the PCF in more detail by summarizing the current state of theory and empirical evidence. In Sect. 3 we show how to incorporate the PCF into DICE-2013R and how to calibrate the new PCF-related parameters. In Sect. 4 we discuss some empirical results derived from our extended model, and in Sect. 5 we summarize the paper.

2 The permafrost carbon feedback

Permafrost is soil (sediment or rock) which remains below 0 °C for 2 or more years and covers about a quarter of the northern hemispheric land surface. Especially in the high-latitude permafrost regions temperatures have risen 0.6 °C per decade over the last 30 years, which is twice as fast as the global average (IPCC 2013). Thus,

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[4] See http://www.econ.yale.edu/~nordhaus/homepage/.

[5] The term "tipping point" refers to critical thresholds where earth's climate abruptly moves between relatively stable states. When the system is already close to such a tipping point, even small changes in temperature can have dramatic consequences which are hard to predict. Examples are the melt of the Greenland ice sheet, the shutoff of the Atlantic deep water formation or the collapse of the Indian summer monsoon (Lenton et al. 2008).

permafrost regions are very sensitive to global climate change. Moreover, in these regions soils have the highest mean soil organic carbon contents. Boreal and Arctic ecosystems contain approximately 50% of global terrestrial organic carbon below ground (Tarnocai et al. 2009). At higher latitudes, these are frozen over by permafrost, and the embedded greenhouse gases are effectively locked away. However, when the soil thaws due to rising temperatures, the greenhouse gases will become unlocked and be released as carbon dioxide and methane due to the microbial decomposition of organic carbon. These additional emissions accumulate in the atmosphere, accelerate global warming and constitute the PCF.

However, uncertainties exist about the timing and the range of the potential carbon release (Bradford et al. 2016) as the details of the decomposition processes, the quality of soil carbon and the horizontal and vertical distribution of soil carbon are not entirely known (Burke et al. 2012). Further sources of uncertainty include differences in snow and organic matter properties, the spatial variability of thawing permafrost, the amount of thawed carbon which decomposes into carbon dioxide or into methane and the assumptions about the initial carbon stock as the effects of increasing temperatures are contingent.[6] Higher carbon fluxes (e.g., Schaefer et al. 2011) are due to faster permafrost degradation simulations. As a consequence, estimates about the permafrost sensitivity, which describes the carbon release per degree of warming, differ considerably and range from 20 to 177 Gt/°C (Friedlingstein et al. 2006). Additionally, negative feedbacks might be triggered, as increasing decomposition in thawing permafrost can lead to a higher nitrogen availability which in turn can intensify plant growth, mitigating previous carbon losses (Koven et al. 2015). Although this effect is regarded as rather small, it highlights further uncertainties.

Despite the uncertainties discussed above, it is obvious that the PCF leads to irreversible consequences. According to a survey by Schuur et al. (2015) different climate models using the RCP 8.5 scenario[7] (as most studies do) estimate that the carbon release from thawing permafrost by the year 2100 will lie in the range of 37–174 Gt carbon with an average of 92 ± 17 Gt. Moreover, a study by MacDougall et al. (2012) which is not included in the survey above estimates a maximum carbon release between 68 and 508 Gt by the year 2100. In contrast, as will be justified in more detail below, our analysis is based on a rather conservative estimate by Schneider von Deimling et al. (2012) indicating a carbon release of 63 Gt by the year 2100 which is even below the above mentioned average of 92 ± 17 Gt.

There is clear evidence that the additional carbon release due to the PCF leads to an enhanced surface warming but the estimated values differ considerably due to the uncertainties discussed above. Most studies that investigate the impact of thawing permafrost on temperature refer to the high concentration pathway RPC8.5. Schaefer et al. (2014) show by comparing 14 published estimates on impacts of the

[6] According to Schuur et al. (2015) these assumptions range from 500 Gt to 1488 Gt carbon.

[7] The abbreviation RCP refers to the four "Representative Concentration Pathways" (RCP2.6, RCP4.5, RCP6, RCP8.5) that describe greenhouse gas concentration trajectories used for climate modeling. These scenarios define different radiative forcing values (2.6, 4.5, 6.0, 8.5 W/m^2) by the year 2100 relative to pre-industrial values in 1850 (see van Vuuren et al. 2011).

Table 1 Additional increase in atmospheric temperature due to the PCF in the years 2100 and 2200 for different RCP emission scenarios (Schneider von Deimling et al. 2012)

	Lower boundary		Best guess		Upper boundary	
	2100 (°C)	2200 (°C)	2100 (°C)	2200 (°C)	2100 (°C)	2200 (°C)
RCP2.6	0.01	0.03	0.03	0.06	0.06	0.13
RCP4.5	0.02	0.07	0.05	0.14	0.10	0.29
RCP6.0	0.02	0.10	0.05	0.20	0.11	0.46
RCP8.5	0.04	0.18	0.10	0.38	0.23	0.78

PCF on global temperatures based on RCP8.5 scenarios values from 0.13 °C up to 0.7 °C by the year 2100. Burke et al. (2012) calculate for the same period a temperature increase between 0.08 and 0.36 °C for RCP8.5 and between 0.02 and 0.11 °C for RCP2.6 (each referring to the 5th to 95th percentile). These values are slightly higher compared to the median estimates (68% range) by Schneider von Deimling et al. (2012) shown in Table 1.

In principle, each of the studies mentioned above could be used for calibrating our extension of DICE-2013R. However, due to three reasons we decided to use the estimates of Schneider von Deimling et al. (2012) shown in Table 1. First, the authors provide the most comprehensive assessment of the temperature increase caused by the PCF considering different RCP scenarios and multiple points in time. Second, the authors did calculate not only a "best guess" for each RCP scenario but they also specified an upper and lower boundary. And third, compared to other studies the estimates of Schneider von Deimling et al. (2012) are rather conservative which ensures that our results will not overrate the consequences of the PCF.

3 Integrating the PCF into DICE-2013R

When modeling climate feedback mechanisms it is most important to account for their self-enforcing character: An increase in temperature triggers a feedback mechanism which leads to a further increase in temperature. Consequently, for integrating the PCF into the mathematical setup of DICE-2013R we include the atmospheric temperature increase $\Delta T_{AT}(t)$ as an additional endogenous argument into the equation which describes greenhouse gas emissions $E(t)$:

$$E(t) = E_{\mathrm{ind}}(t) + E_{\mathrm{def}}(t) + \varepsilon_1(t) \times \Delta T_{\mathrm{AT}}(t)^{\varepsilon_2(t)}. \tag{1}$$

The variables $E_{\mathrm{ind}}(t)$ and $E_{\mathrm{def}}(t)$ represent endogenous emissions from industrial processes and exogenous emissions from land use changes as in the original model, and our extension $\varepsilon_1(t) \times \Delta T_{\mathrm{AT}}(t)^{\varepsilon_2(t)}$ causes the respective feedback loop:[8] Due to increasing temperatures $\Delta T_{AT}(t)$ the permafrost thaws step by step which leads to an increased release of greenhouse gases depending on the parameters $\varepsilon_1(t) > 0$ and

[8] Our extension in (1) represents the simplest functional form that suffices to meet the requirements as described in the calibration section.

$\varepsilon_2(t) > 0$.[9] As a result, the greenhouse gas concentration in the atmosphere intensifies which leads to further rising temperatures and a further thawing of permafrost.

In the next step, a reliable calibration of $\varepsilon_1(t)$ and $\varepsilon_2(t)$ requires that our extended version of DICE-2013R is able to reproduce the temperature increase caused by the PCF as estimated by Schneider von Deimling et al. (2012). Their estimates, however, are based on the assumption that climate policy does not respond to the PCF. Consequently, to ensure compatibility with them, for our calibration runs we have to fix the mitigation rates in the extended version of DICE-2013R to the magnitudes resulting from the original DICE-2013R which does not account for the PCF. The accumulated emissions as well as the radiative forcing resulting from the original model represent a close match of the respective magnitudes assumed in the RCP4.5 scenario.[10] Therefore, we use the RCP4.5 estimates of Schneider von Deimling et al. (2012) for calibrating $\varepsilon_1(t)$ and $\varepsilon_2(t)$.

Following the approach outlined above, we fixed the mitigation rates according to the outcome of the original DICE-2013R model and calculated the temperature increase resulting from these fixed rates in our extended version of DICE-2013R.[11] This proceeding ensures that climate policy in the calibration runs ignores the PCF as assumed by Schneider von Deimling et al. (2012). Next, we run this setup multiple times resetting the parameters $\varepsilon_i(t)$ each time until the additional temperature increase caused by the PCF in the years 2100 and 2200 resulted exactly in the "best guess"-magnitudes for the RCP4.5 scenario shown above in Table 1. Moreover, for the starting year 2010 we required an additional temperature increase of zero which is also in line with the underlying study of Schneider von Deimling et al. (2012). Finally, we repeated this procedure for the lower as well as for the upper boundary estimates shown in Table 1.

The parameters $\varepsilon_i(t)$ resulting from our calibration are shown in Table 2 for the best guess scenario as well as the lower and the upper boundary scenario. These expressions look somewhat peculiar due to the variable ord(t) which is part of the GAMS syntax. It simply displays the number of the period that is currently considered [e.g., in period 10 we obtain ord(t) = 10]. This time-dependent formulation is necessary to meet the estimates by Schneider von Deimling et al. (2012). The reasons for this complication are twofold: On the one hand, the long residence time of greenhouse gases in the atmosphere entails that additional emissions due to thawing permafrost take effect for many subsequent periods. On the other hand, when a certain degree of warming is reached, the majority of the

[9] As will be explained below, the additional parameters $\varepsilon_1(t)$ and $\varepsilon_2(t)$ must be time-dependent to allow for a reliable calibration.

[10] More precisely, the accumulated emissions and the radiative forcing of the original DICE-2013R model are slightly above the respective values of RCP4.5 and considerably below RCP6.0. Consequently, using the RCP4.5 estimates of Schneider von Deimling et al. (2012) for calibrating ε_i implies that we slightly underrate the impacts of the PCF. In contrast, using the RCP6.0 estimates would lead to considerably overrating these impacts.

[11] All calculations in this paper have been processed with the GAMS-software ("general algebraic modeling system") using the CONOPT-3 solver. This is the same setup that is used by Nordhaus (2013) for solving the DICE-2013R model. The program file is available from the corresponding author on request.

Table 2 Calibration results for the parameters ε_1 and ε_2 based on the RCP4.5 scenario

	Lower boundary	Best guess	Upper boundary
ε_1	$0.75\mathrm{Ord}(t)^{-1}$	$2.55\mathrm{Ord}(t)^{-1}$	$5.2\mathrm{Ord}(t)^{-1}$
ε_2	$2.9 + 2\mathrm{Ord}(t)^{-1}$	$2.35 + 2\mathrm{Ord}(t)^{-1}$	$2.35 + 2\mathrm{Ord}(t)^{-1}$

permafrost has already thawed and less additional emissions are released into the atmosphere. Taken together, these two effects imply that the additional increase in temperature caused by the PCF follows a logistic trend in time, which is disproportionately high during the first part of the time horizon and disproportionately low afterwards. Consequently, with constant parameters ε_i we would meet either the estimate for 2100 or the estimate for 2200, but never both. In contrast, the time-dependent expressions in Table 2 become smaller over time because ord(t) increases. As a result, the impact of the PCF is diminishing in the long run as it is projected by the natural sciences.

To demonstrate the validity of our calibration, Fig. 1 shows the additional increase in temperature due to the PCF that results if we employ the parameter values $\varepsilon_i(t)$ that stem from our calibration runs using the best guess scenario. Additionally, the three points marked by the symbol Δ represent the underlying estimates by Schneider von Deimling et al. (2012) which are in line with our simulation results. Moreover, the turning point in the graph shown in Fig. 1, where the additional temperature increase becomes disproportionately low, occurs by the year 2150. This is also consistent with Schneider von Deimling et al. (2012) who estimate that most of the emissions caused by thawing permafrost will occur roughly up to 2150.

Finally, before presenting our empirical results it is necessary to distinguish our analysis from the work recently published by Gonzáles-Eguino and Neumann (2016). Except for some technical features, there are three main differences:

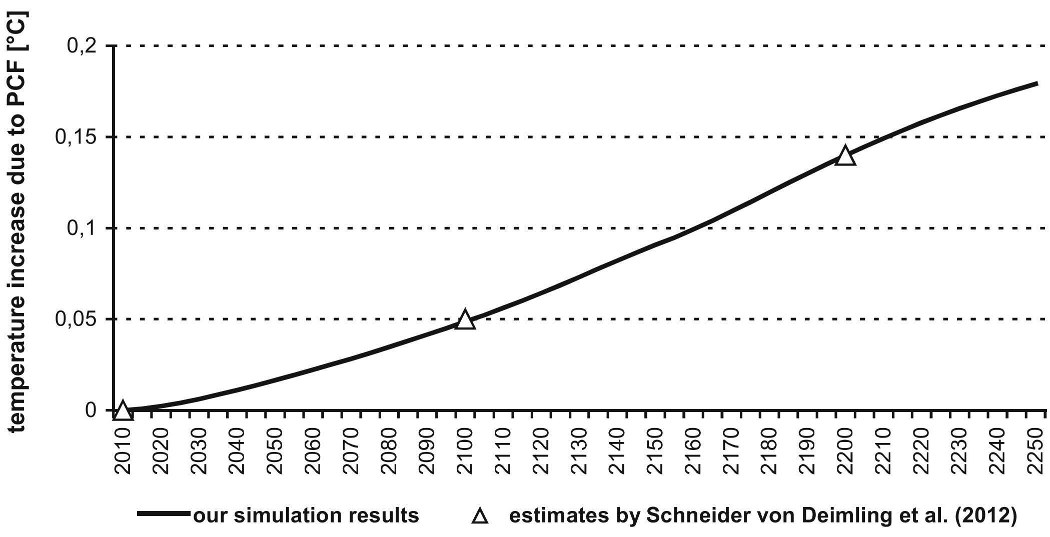

Fig. 1 Temperature increase due to the PCF in the best guess scenario: comparing our simulation results with the estimates of Schneider von Deimling et al. (2012)

- First, Gonzáles-Eguino and Neumann (2016) use a carbon budget approach where the temperature increase is handled as an additional restriction and kept below 2 °C. For this constrained scenario, the authors calculate the welfare maximizing mitigation rates. In contrast, we follow the original approach of DICE-2013R and calculate the unconstrained welfare maximum. Hence, in our analysis the resulting increase in temperature is completely endogenous.
- Second, in the work of Gonzáles-Eguino and Neumann (2016) emissions from permafrost follow an exogenously given time path, whereas in our analysis PCF-related emissions explicitly depend on temperature thereby constituting an endogenous feedback loop.
- Third, Gonzáles-Eguino and Neumann (2016) calculate the increase in mitigation rates and the associated cost to society that occur if the 2 °C target has to be met in the presence of emissions from permafrost. In contrast, we also calculate the economic losses resulting from a mitigation policy which ignores the PCF.

4 Results for the PCF

In this section, we discuss the results from using the DICE-2013R model with the PCF extension as described above and compare them to the original results of Nordhaus (2013). The major endogenous policy variables are the mitigation rates $\mu(t)$ which describes the share of emissions avoided. Figure 2 shows the "base level" of the mitigation rates resulting from the original DICE-2013R model as calculated by Nordhaus (2013).[12] For the first period (i.e., the year 2010) the mitigation rate is exogenously fixed. The first endogenously optimized mitigation rate occurs in the year 2015 with roughly 20%. From that point on, the mitigation rate rises steadily until it reaches its (temporary) upper limit of 100% in the year

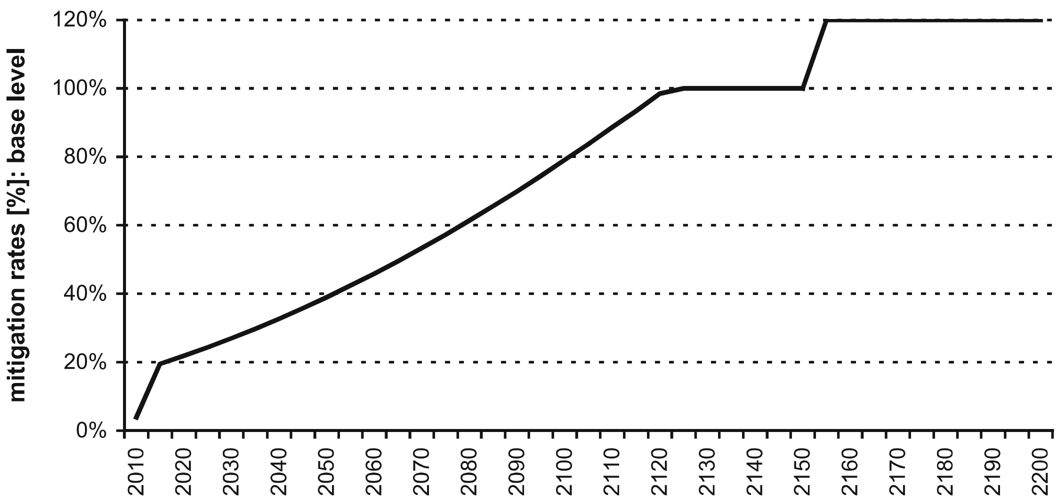

Fig. 2 Optimal mitigation rates in the original DICE-2013R model ("base level")

[12] For convenience, in the text as well as in the figures mitigation rates are expressed as percentages although in the original GAMS file the variables $\mu(t)$ are expressed as decimals.

2120. Subsequently, beginning in 2155 the upper limit is relaxed to 120% which causes another jump in Fig. 2. Of course, mitigation rates above 100% imply that more emissions are avoided than even occurring. This could be interpreted as the employment of some carbon removal techniques which become available by 2155 (e.g., climate engineering).[13]

Next, we present the results of our own calculations using the DICE-2013R model with the PCF extension for the best guess scenario as well as for the upper and the lower boundary.[14] To enhance the graphical depiction, Fig. 3 does not show the absolute mitigation rates but their difference to the base levels as shown in Fig. 2. As indicated by Fig. 3, in all scenarios the resulting mitigation rates are slightly above the base levels.[15] The reason for this difference is obvious: The PCF leads to increased emissions, and therefore, to increasing climate damages. Hence, mitigation becomes more favorable.

For all three scenarios the mitigation rates' differences to the base level increase steadily until they drop down to zero in 2125 since mitigation rates approach to their upper limit in our extended model as well as in the original version. The differences to the base level are biggest in the upper boundary scenario where the PCF is most severe. In this scenario, the differences rise up to roughly 2.7% points. This might seem to be rather small but two crucial points need to be emphasized. First, as already mentioned in Sect. 2, the magnitudes concerning the PCFs impact on the temperature as shown in Table 1 are quite conservative guesses compared to other studies. And second, our model considers only one type of feedback mechanism; when multiple feedbacks are considered simultaneously, the overall impact could be expected to be much higher.

Also the differences shown in Fig. 3 are small compared to the results of related papers investigating uncertainty and potential catastrophes (Keller et al. 2004; Ackerman et al. 2010). However, these results are only partially comparable. We deal with climate feedbacks that enhance damages but we do not deal with uncertainty about these damages. In contrast, the above cited papers explicitly consider uncertainty leading to much higher emission mitigation rates that can be considered as a risk premium to insure against catastrophes (Nordhaus 2008 pp. 137; Weitzman 2010).

An important variable directly related to the mitigation rate is the temperature increase. Although our extended model leads to higher mitigation rates compared to Nordhaus (2013) the corresponding atmospheric temperature exceeds the base level resulting from the original version of DICE-2013R. These differences in

[13] However, neither Nordhaus (2013) nor Nordhaus and Sztorc (2013) offer an explicit justification for relaxing the upper limit in 2155.

[14] It should carefully be noted, that the fixation of the mitigation rates $\mu(t)$ to the *base* level in Sect. 3 was only for the purpose of calibrating the parameters ε_i. The results discussed here, of course, rely on endogenously optimized mitigation rates.

[15] Generally, the PCF-related increase in mitigation rates calculated with our approach is smaller compared to the results obtained by Gonzáles-Eguino and Neumann (2016). The reason is that their model forces the increase in temperature to stay below 2 °C, whereas unconstrained welfare maximization in our model leads to a peak increase in temperature of about 3.4 °C.

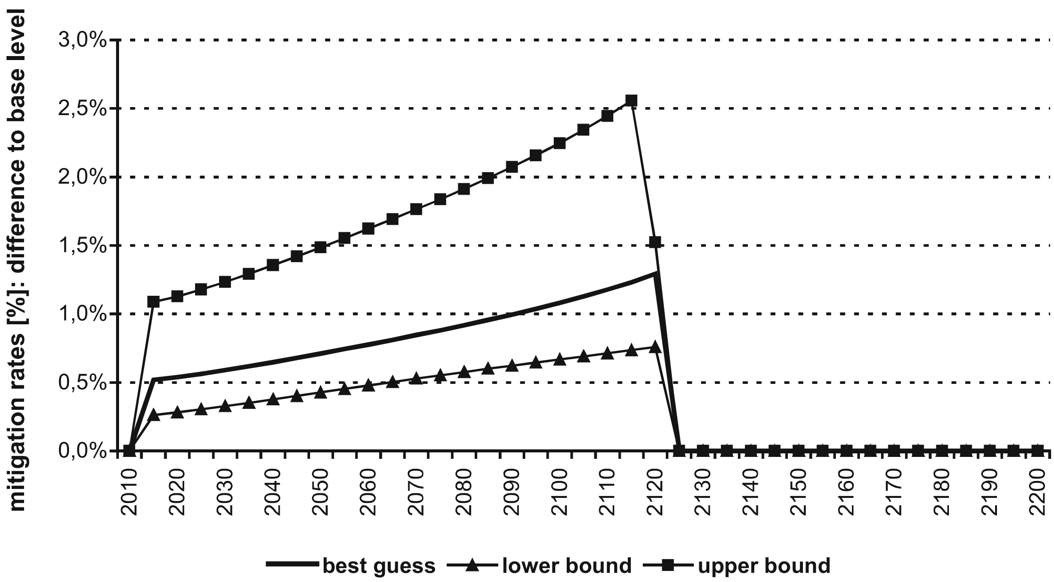

Fig. 3 Difference between optimal mitigation rates with PCF and base level mitigation rates according to Fig. 2

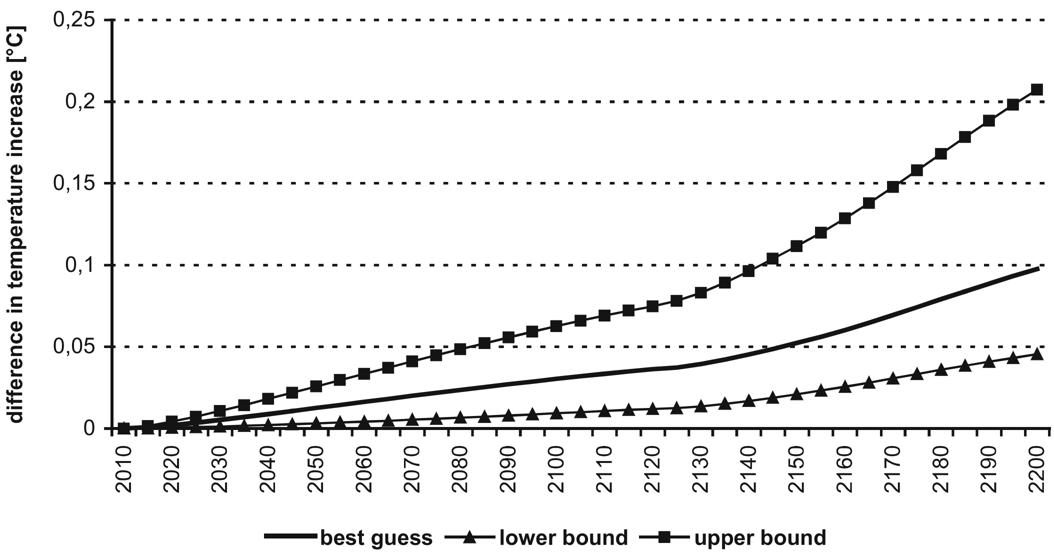

Fig. 4 Temperature increase—difference between our results with optimized mitigation rates and the original DICE2013R model

temperature, as shown in Fig. 4, indicate that even in the optimum, enhanced mitigation will only avoid a part of the temperature increase caused by the PCF. However, as easily can be checked, the additional increase in temperature that remains after enhanced mitigation stays well below the reference values for the RCP4.5 scenario presented in Table 1.

Next, to investigate potential economic impacts, we compute the output losses that are caused if climate policy ignores that optimal adaption to the PCF requires increasing mitigation rates. Each calculation for the best guess scenario as well as for the upper and the lower boundary proceeds in three steps:

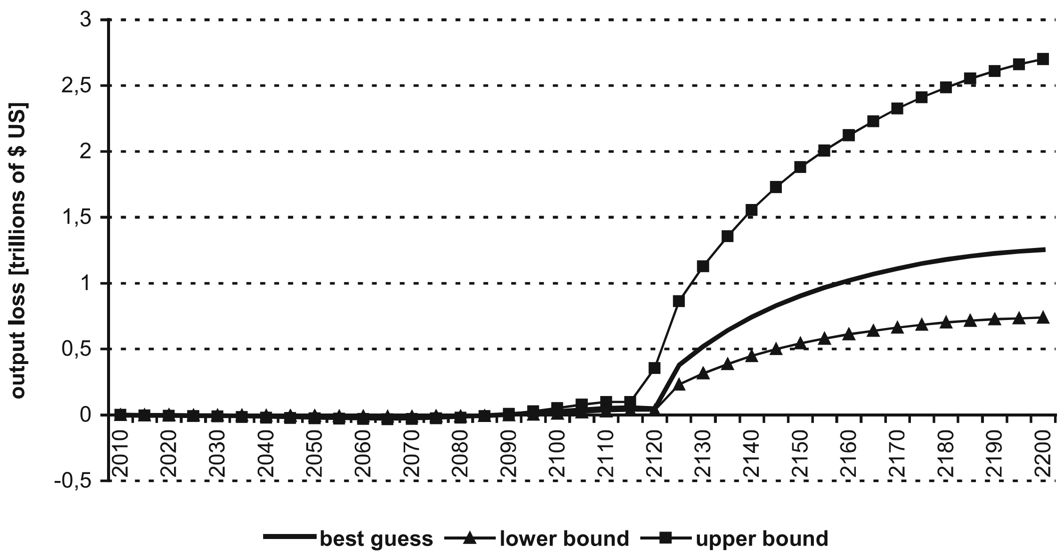

Fig. 5 Output loss that is caused if climate policy ignores the PCF

- In the first step, we calculate the output that results if the optimal mitigation rates as derived from our extended model are employed.
- In the second step, the mitigation rates are fixed to the reference values (base level) that stem from the original DICE-2013R without the PCF. Hence, our model is forced to employ suboptimal low mitigation rates. This yields the output that results if climate policy ignores the PCF although its mechanism is present in the model.
- In the third step, the differences in output between the optimal run (first step) and the run with fixed mitigation rates (second step) are calculated. These differences can be interpreted as the economic losses that occur if the PCF is ignored.

The undiscounted losses in output (trillions of $US) resulting from these calculations are shown in Fig. 5.[16] Noticeable, the economic impact for roughly the first 100 years is very small since output losses tend to be around zero or even slightly below in all three scenarios. Negative losses imply that actually the suboptimal climate policy with fixed mitigation rates is economically beneficial in those periods. The reason for this is obvious: The optimal climate policy requires higher mitigation rates. This leads immediately to higher mitigation costs, whereas the majority of the benefits in terms of a lower atmospheric carbon concentration accrue in the distant future. Consequently, when considering only the first couple of periods, employing suboptimal low mitigation rates is beneficial.

However, things change drastically by the year 2125 when the graphs suddenly get steeper and output losses become considerably positive. This turn can easily be explained: As indicated by Fig. 3, in 2125 the optimal mitigation rates converge to the base level rates shown in Fig. 2. Hence, in the following years there are no more

[16] The same calculations can be performed for the variables consumption and investment. The resulting diagrams are mostly similar to those for output.

additional mitigation costs implied by the optimal policy but the economy still profits from the increased mitigation rates in the past.

Finally, we calculated the net present value of output losses employing a pure rate of social time preference of 1.5% as used by Nordhaus (2013). The resulting magnitudes range from 0.9 trillion $US in the lower boundary scenario, to 1.5 trillion $US in the best guess scenario and 3.2 trillion $US in the upper boundary scenario. Compared to the overall net output this implies relative losses ranging from 0.02 to 0.08%. These figures might seem pretty low. However, since the benefits of taking into account the PCF when determining the optimal mitigation rates occur in the distant future, there is an enormous bias caused by discounting. Moreover, as already mentioned above, our results are based on rather conservative estimates of the impact on temperature caused by the PCF.

5 Conclusions

Previous studies on the economics of climate change based on integrated assessment models almost completely omitted the additional effects of feedback mechanisms within the climate system. From the viewpoint of integrated assessment modeling, the most important feature of these mechanisms is their self-enforcing character which leads to endogenous feedback loops. In this paper, we focused on the permafrost carbon feedback (PCF) which is one of the most studied and best understood climate feedback mechanisms. We showed how to incorporate the PCF into DICE-2013R and how to calibrate the new parameters. Subsequently, we derived some empirical results concerning the economic impacts of the PCF.

Our results showed that maximizing welfare in the presence of an endogenous feedback loop caused by PCF-related emissions requires an increase in mitigation rates that amounts up to 2.7% points (depending on the scenario considered). At first glance, this might seem rather small. However, analyzing multiple feedback mechanisms simultaneously should considerably amplify the impacts illustrated. Moreover, our results are based on rather conservative estimates concerning the impact of the PCF on temperature.

Concerning overall welfare we calculated the economic losses resulting from a mitigation policy which ignores the PCF. It turned out that the main losses occur far in the future when mitigation rates with and without considering the PCF converge such that there are no more additional mitigation costs but the economy would still profit from increased (optimal) mitigation rates in the past. Moreover, this delayed occurrence of losses together with the impact of discounting leads to comparatively small economic effects ranging from −0.02 to −0.08% when the present value of output is considered.

Of course, we are aware that our analysis can provide only some first insights concerning the incorporation of endogenous feedback loops into integrated assessment models and the resulting economic consequences. Except for the PCF there is still huge uncertainty about the different feedback mechanisms' quantitative impacts on the climate system. Consequently, more studies from the natural sciences are necessary before these mechanisms can be properly calibrated and included into integrated assessment models like DICE.

Appendix: Short description of the DICE-2013R model

The utility in DICE is expressed as a standard constant-relative-risk-aversion utility function for neoclassical growth models:

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

with t indicating the specific period (one period accounts for 5 years), $c(t)$ is per capita consumption, $L(t)$ is the population and α is the elasticity of marginal utility of consumption. The objective is to maximize the welfare function W. The latter consists of the discounted utility summed over a finite time horizon:

$$W[c(t),\ L(t)] = \sum_{t=1}^{T} \frac{1}{(1+\rho)^{t-1}} U[c(t), L(t)]. \tag{2}$$

The parameter ρ is the pure rate of social time preference such that $1\big/(1+\rho)^{t-1}$ is the discount factor. The production function is of Cobb–Douglas type:

$$Y(t) = A(t)K(t)^{\gamma}L(t)^{1-\gamma}. \tag{3}$$

$A(t)$ is the total factor productivity, $K(t)$ is the capital stock, $L(t)$ is not only the population but also the labor input and γ is the elasticity of output with respect to capital. The link to the climate module is formed via greenhouse gas emissions which are caused by production due to an exogenous emission coefficient [see also Eq. (7)]. These emissions accumulate in the atmosphere. The carbon dioxide concentrations in the atmosphere and in the oceans are interrelated, since oceans are considered a huge sink for emissions (Nordhaus 2008 p. 43). As described below by Eqs. (9)–(14), the accumulated emissions lead to a higher atmospheric greenhouse gas concentration which causes the radiative forcing to increase and ultimately cause the surface temperature to increase. The impact of this temperature increase is given by the following damage function $\Omega(t)$ which indicates the share of output that is lost due to climate damages:

$$\Omega(t) = \sigma_1 \times \Delta T_{AT}(t) + \sigma_2 \times \Delta T_{AT}(t)^2. \tag{4}$$

$\Delta T_{\mathrm{AT}}(t)$ is the increase of the atmospheric global mean temperature compared to the pre-industrial level, and σ_1 as well as σ_2 are parameters that determine the shape of the damage function. To avoid damages, emissions can be reduced by mitigation activities. The accompanying costs $\Lambda(t)$ are expressed as the share of output that is lost due to mitigation activities. The cost function describing $\Lambda(t)$ is given by:

$$\Lambda(t) = \psi_1 \cdot \mu(t)^{\psi_2} \tag{5}$$

with $\mu(t)$ indicating the share of avoided emissions, and ψ_1 as well as ψ_2 are parameters that determine the shape of the mitigation cost function.

To sum up, $\Omega(t)$ indicates the share of output lost due to climate damages, whereas $\Lambda(t)$ indicates the share of output lost due to mitigation activities. Consequently, weighting the gross output $Y(t)$ by the multipliers $[1 - \Omega(t)]$ and $[1 - \Lambda(t)]$ yields the remaining net output:

$$Y_{net}(t) = [1 - \Omega(t)][1 - \Lambda(t)]A(t)K(t)^{\gamma}L(t)^{1-\gamma}. \tag{6}$$

Equation (6) highlights the typical trade-off in climate policy: More emission mitigation leads to higher mitigation costs $\Lambda(t)$ resulting in a decreasing net output. However, at the same time, more emission mitigation leads to lower damages $\Omega(t)$ resulting in an increasing net output.

Finally, the net output is divided into consumption and investment: $Y_{net}(t) = C(t) + I(t)$. This creates the typical trade-off in neoclassical growth models. Output is either consumed directly or invested in physical capital to increase the consumption possibilities in the future.

Emissions are caused by production depending on an exogenous emission coefficient $\tau(t)$ which declines over time to simulate carbon-saving technological change. Accounting for abatement activities, the remaining emissions from production are given by:

$$E_{ind}(t) = \tau(t)[1 - \mu(t)]A(t)K(t)^{\gamma}L(t)^{1-\gamma} \tag{7}$$

with $\mu(t)$ indicating the mitigation rate, i.e., the share of emissions avoided. Besides emissions from production the model also accounts for exogenously given emissions from land use changes (e.g., deforestation) which are denoted by $E_{\mathrm{def}}(t)$. Hence, the complete emissions are given by:

$$E(t) = E_{\mathrm{ind}}(t) + E_{\mathrm{def}}(t). \tag{8}$$

These emissions accumulate in the atmosphere and cause the atmospheric carbon concentration to increase. The latter is interrelated with the concentrations in different layers of the oceans. The concentrations in the atmosphere $M_{\mathrm{AT}}(t)$, in the upper ocean $M_{\mathrm{UO}}(t)$ and in the lower ocean $M_{\mathrm{LO}}(t)$ and their interrelationship are shown in Eqs. (9)–(11):

$$M_{AT}(t) = E(t) + [1 - \varphi_{12}] \times M_{AT}(t-1) + \varphi_{21} \times M_{UO}(t-1), \tag{9}$$

$$M_{UO}(t) = \varphi_{12} \times M_{AT}(t-1) + \varphi_{22} \times M_{UO}(t-1) + \varphi_{32} \times M_{LO}(t-1), \tag{10}$$

$$M_{LO}(t) = \varphi_{23} \times M_{UO}(t-1) + \varphi_{33} \times M_{LO}(t-1). \tag{11}$$

The atmospheric concentration $M_{\mathrm{AT}}(t)$ is composed of the current emissions, the share of the concentration remaining from the previous period plus the share of the upper oceanic concentration from the previous period that diffuses into the atmosphere. The upper oceanic concentration $M_{\mathrm{UO}}(t)$ consists of the remaining share from the previous period plus the absorptions from the atmosphere and the lower oceans. The concentration in the lower oceans $M_{\mathrm{LO}}(t)$ is the remaining share of the previous period plus the absorption from the upper oceans. The parameters φ_{ij} control these relationships between different reservoirs and periods.

In the next step, the atmospheric carbon concentration $M_{\mathrm{AT}}(t)$ increases the radiative forcing from the sun $F(t)$ represented by:

$$F(t) = \eta \times \frac{M_{\mathrm{AT}}(t)}{M_{\mathrm{AT}}(\mathrm{preind})} + F_{\mathrm{exog}}(t) \tag{12}$$

with η being a parameter that controls the impact of increasing greenhouse gas concentrations and $M_{\mathrm{AT}}(\mathrm{preind})$ indicating the pre-industrial level of these concentrations. The term $F_{\mathrm{exog}}(t)$ covers the additional radiative forcing caused by other greenhouse gases or aerosols that are exogenous in the model.

Finally, the increasing radiative forcing results in an increase of temperatures in the atmosphere $\Delta T_{\mathrm{AT}}(t)$ as well as in the oceans $\Delta T_{\mathrm{O}}(\mathrm{t})$ as given by Eqs. (13) and (14):

$$\begin{aligned}\Delta T_{\mathrm{AT}}(t) = {} & \Delta T_{\mathrm{AT}}(t-1) \\ & + \omega_1[F(t) - \omega_2 \Delta T_{\mathrm{AT}}(t-1) - \omega_3(\Delta T_{\mathrm{AT}}(t-1) - \Delta T_O(t-1))],\end{aligned} \tag{13}$$

$$\Delta T_{\mathrm{O}}(t) = \Delta T_{\mathrm{O}}(t-1) + \omega_4[\Delta T_{\mathrm{AT}}(t-1) - \Delta T_{\mathrm{O}}(t-1)]. \tag{14}$$

The change in atmospheric temperatures according to (13) results from the change of the previous period, as well as from the current radiative forcing that is corrected for the previous period and the interference between atmosphere and oceans. Analogously, the temperature change in the oceans according to (14) is computed from the change of the previous period that is corrected for the interference between the oceans and the atmosphere. These relationships between radiative forcing and the temperature in different carbon reservoirs or different periods, respectively, are controlled by the parameters ω_{i}.

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