Climatic Change (2009) 96:313–333
DOI 10.1007/s10584-009-9629-8

Cost–benefit analysis of climate change dynamics: uncertainties and the value of information

Ari Rabl · Bob van der Zwaan

Received: 2 June 2008 / Accepted: 27 May 2009 / Published online: 23 July 2009

Abstract We analyze climate change in a cost–benefit framework, using the emission and concentration profiles of Wigley et al. (Nature 379(6562):240–243, 1996). They present five scenarios that cover the period 1990–2300 and are designed to reach stabilized concentration levels of 350, 450, 550, 650 and 750 ppmv, respectively. We assume that the damage cost in each year t is proportional to the corresponding gross world product and the square of the atmospheric temperature increase ($\Delta T(t)$). The latter is estimated with a simple two-box model (representing the atmosphere and deep ocean). Coupling the damage cost with the abatement cost, we interpolate between the five scenarios to find the one that is optimal in the sense of minimizing the sum of discounted annual (abatement plus damage) costs over a time horizon of N years. Our method is simpler than 'traditional' models with the same purpose, and thus allows for a more transparent sensitivity study with respect to the uncertainties of all parameters involved. We report our central result in terms of the stabilized emission level E_o and concentration level p_o (i.e. their values at $t = 300$ years) of the optimal scenario. For the central parameter values (that is, $N = 150$ years, a discount rate $r_{dis} = 2\%$/year and a growth rate $r_{gro} = 1\%$/year of gross world product) we find $E_o = 8.0$ $GtCO_2$/year and $p_o = 496$ ppmv. Varying the parameters over a wide range, we find that the optimal emission level remains within a remarkably narrow range, from about 6.0 to 12 $GtCO_2$/year for all plausible parameter values. To assess

A. Rabl
Centre Energétique et Procédés, Ecole des Mines,
60 boulevard St. Michel, 75272, Paris, Cedex 06, France
e-mail: ari.rabl@gmail.com

B. van der Zwaan (✉)
Policy Studies Department, Energy research Centre of the Netherlands,
P.O. Box 56890, 1040 AW, Amsterdam, The Netherlands
e-mail: vanderzwaan@ecn.nl

B. van der Zwaan
Lenfest Center for Sustainable Energy, The Earth Institute, Columbia University,
500 West 120th Street, New York, NY 10027, USA

the significance of the uncertainties we focus on the social cost penalty, defined as the extra cost incurred by society relative to the optimum if one makes the wrong choice of the emission level as a result of erroneous damage and abatement cost estimates. In relative terms the cost penalty turns out to be remarkably insensitive to errors. For example, if the true damage costs are three times larger or smaller than the estimate, the total social cost of global climate change increases by less than 20% above its minimum at the true optimal emission level. Because of the enormous magnitude of the total costs involved with climate change (mitigation), however, even a small relative error implies large additional expenses in absolute terms. To evaluate the benefit of reducing cost uncertainties, we plot the cost penalty as function of the uncertainty in relative damage and abatement costs, expressed as geometric standard deviation and standard deviation respectively. If continued externality analysis reduces the geometric standard deviation of relative damage cost estimates from 5 to 4, the benefit is 0.05% of the present value G_{tot} of total gross word product over 150 years (about $\$3.9 \times 10^{15}$), and if further research reduces the standard deviation of relative abatement costs from 1 to 0.5, the benefit is 0.03% of G_{tot}.

1 Introduction

Even if a comparison of costs and benefits may not be the only relevant criterion for the design and implementation of environmental policy, it is a crucial input. For the case of climate change it is thus advisable to quantify the costs and benefits of CO_2 emissions abatement as much as possible, as done in the landmark Stern Review (Stern et al. 2006). The usefulness of cost–benefit analysis (CBA) for assessing environmental policy such as relating to climate control has often been questioned, given the notoriously large uncertainties involved. We countered those queries in earlier work, by showing, for several pollutants including CO_2, that the cost penalty incurred by making the wrong abatement choice because of uncertainties in the estimates for the costs and benefits of environmental policy is remarkably small (Rabl et al. 2005; van der Zwaan and Rabl 2009). Hence, CBA can be useful despite large uncertainties. The present paper extends our earlier static analyses to a dynamic non-linear CBA model for climate change, which we consider more realistic and more appropriate.

Ideally climate change CBA should identify the optimal scenario of greenhouse gas emissions as a function of time, by minimizing the present value of the sum of damage cost and abatement cost. That would require detailed models for the time dependence of these costs as function of the (time-dependent) emissions, as well as the search of an optimal emission path, certainly a complex and challenging task (Meehl et al. 2007). For a systematic and complete analysis of all uncertainties involved in climate change CBA we consider the ‘traditional’ highly detailed (multi-region, multi-gas, multi-technology) models so complicated, that a sensitivity analysis would become rather opaque and necessarily incomplete. As an alternative we make the following simplifying assumptions:

(1) We consider only CO_2, not the other greenhouse gases such as methane and nitrous oxide.

(2) We assume that the optimal emission scenario is a scaled version of the five scenarios by Wigley et al. (1996) for the period 1990–2300 (here designated by WRE). The WRE scenarios are designed to stabilize atmospheric CO_2 concentrations at levels of 350, 450, 550, 650 and 750 ppmv, respectively. The corresponding emissions and concentrations are shown in Fig. 1a, b.

(3) We assume that the damage cost $c_{dam}(t)$ in each year t is proportional to the corresponding gross world product $G(t)$ and the square of the atmospheric temperature increase $\Delta T(t)$. The latter is estimated with a simple two-box model (representing the atmosphere and deep ocean).

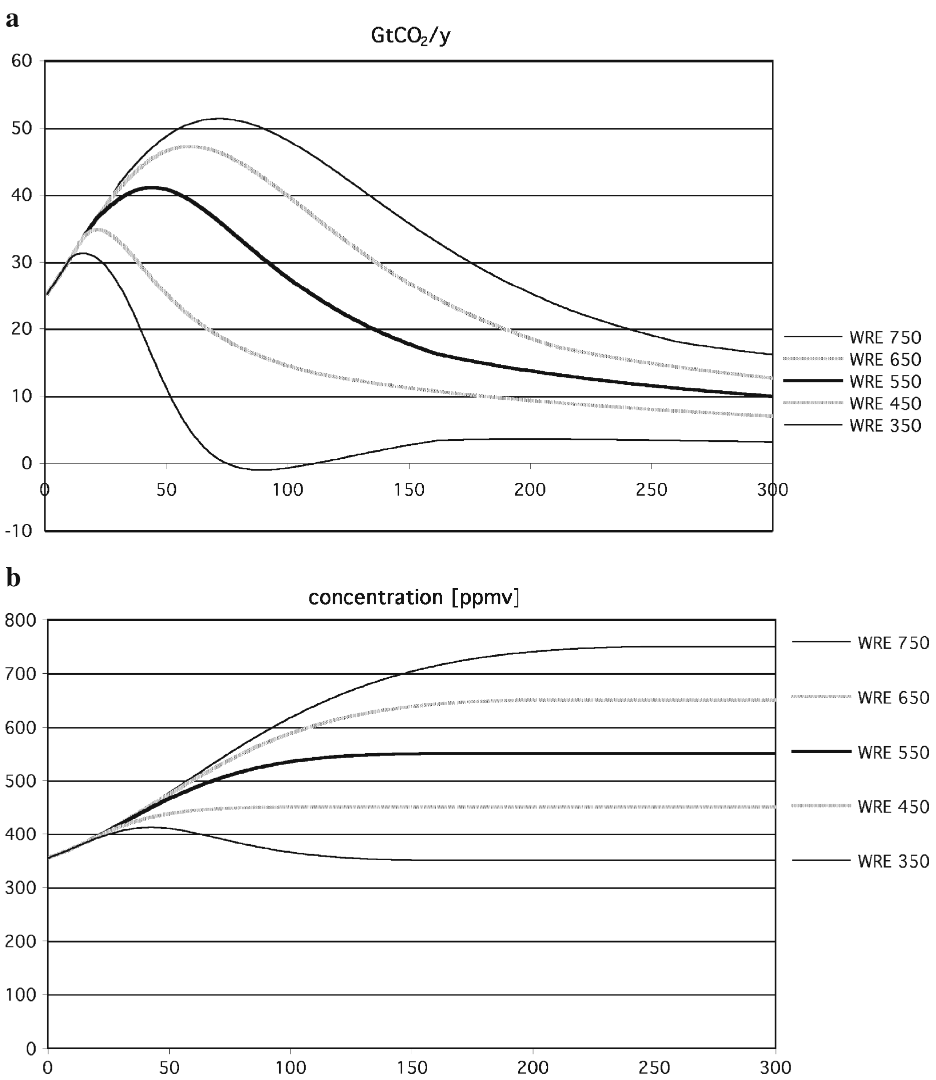

Fig. 1 The stabilization scenarios of Wigley et al. (1996): **a** Emissions, **b** Concentrations

(4) We assume a simple model for the marginal abatement cost per ton of CO_2 as function of emissions E, based on an extensive review of the literature.
(5) Using the 750 ppmv scenario as reference, the total abatement cost in year t (denoted by $c_{ab}(t)$) is calculated as the cost of reducing the reference emissions to the levels of the respective scenarios.
(6) The annual abatement costs $c_{ab}(t)$ and damage costs $c_{dam}(t)$ are discounted at rate r_{dis} and summed over a time horizon of N years to obtain the total costs C_{ab} and C_{dam} for each scenario.
(7) We construct functions $C_{ab}(E)$ and $C_{dam}(E)$ to interpolate the respective costs between the five scenarios. As scaling variable E for the emission scenarios we choose the (nearly asymptotic) emissions in year 300.
(8) We find the optimal level E_o by searching for the minimum (with respect to E) of the total life cycle cost, defined as the sum of C_{ab} and C_{dam}:

$$C_{tot}(E) = C_{dam}(E) + C_{ab}(E) \tag{1}$$

We present most of our results for the costs as fraction of gross world product rather than as monetary values, because the time horizon is so long that the latter would not be very meaningful. Thus our estimates of marginal abatement costs are also to be seen relative to gross world product rather than as absolute monetary values.

Since our model involves only few parameters that express the key features of the problem, we can carry out a CBA that is transparent and shows clearly the uncertainties due to each of the major factors involved. Our work is complementary to that of many, notably to recent publications like DEFRA (2004, 2005) and Tol (2005), in which overviews are given of estimated climate change damage costs under a specified increase in atmospheric CO_2 concentration or average global temperature. We, by contrast, optimize the emission level E over a large range of possible parameter values.

Of course, since our model is based on the emission profiles of Wigley et al. (1996), it does not indicate the optimal rate at which one should reduce emissions towards that long-term goal. That question can be answered through the numerous dynamic studies that have analyzed the time-dependent relation between emission scenarios and climate impacts (see, notably, Baker 2005; Heal and Kriström 2002; Keller et al. 2004; Kolstad 1996; Nordhaus and Popp 1997; Peck and Teisberg 1993; van der Zwaan and Gerlagh 2006).

Whereas the uncertainties of CO_2 abatement costs are large, especially when projected far into the future (typically a factor of 3), those of the damage costs are significantly larger (as much as an order of magnitude). We therefore first provide, in Section 2.1, a concise summary of some of the recent literature reporting estimates for aggregated climate change damage costs. We subsequently develop our expressions for the damage and abatement costs, in Sections 2.2 and 2.3. In Section 3 we present the solution for the optimal emission level E_o as function of our model's key input parameters. To evaluate the consequences of uncertainties, we calculate in Section 4 the cost penalty, defined as the extra social cost incurred relative to the social optimum, as function of the error in the estimates of relative damage and abatement costs. We also estimate the value of reducing these uncertainties through further research, by plotting the cost penalty as function of the geometric standard deviation of the damage cost distribution (assumed lognormal) and as function of the standard deviation of the abatement cost distribution (assumed normal). In Section 5 we summarize our main results, compare them with the Stern review (Stern et al. 2006), and give recommendations for climate change research and policy making.

2 Damage and abatement costs

2.1 Review of damage cost estimates

A large number of integrated assessment models have been developed to assess climate change damage costs and their evolution over time.[1] Some are based directly on the impact of ΔT on Gross Domestic Product (GDP) or Gross World Product (GWP). Others, in particular FUND (Tol 1995) and PAGE (Plambeck and Hope 1996), attempt to simulate climatic impacts in more detail, according to the categories or economic sectors to which they apply. Quite generally, the reported damage cost estimates do not cover all possible climate change impacts. In particular they usually exclude many of the non-market impacts, as well as the possibility of major catastrophes or socially contingent effects. For the economic assessment of catastrophic climate change impacts CBA as used in these models is problematic (see Weitzman 2009 and Yohe 1996).

One of the pioneering models in this field was DICE (Nordhaus 1991, 1994). DICE optimizes the trade-off between the costs of climate change and the costs of restricting CO_2 emissions. The damage cost simulation of DICE assumes that a 3°C warming induces a 0.25% loss of GDP in the USA, based on estimates of market damages such as crop loss, forestry impact, and shoreline erosion. This value is raised to 1% to account for all probable damages, especially non-market ones that are generally hard to quantify. In order to render DICE applicable globally the relative loss is further increased to 1.3% of GWP, as many less developed countries are more dependent on e.g. agriculture and have as such a more limited ability to adapt to the effects of climate change. Furthermore, Nordhaus recognizes that for temperature rises higher than 3°C disproportionally large damages are likely to result, so that the use of a quadratic function is appropriate. Most of the subsequent climate-economy models have adopted a similar climate change damage cost formulation. The non-linear dependence of climate damage on temperature change has been shown by many studies, for instance Schlenker and Roberts (2006).

Another widely used climate policy assessment model is MERGE, a multi-region Ramsey–Solow optimal growth model including greenhouse gas emissions and a global climate module (Manne and Richels 2004). It can be operated in a cost–benefit mode, in which a time path is chosen for emissions that maximizes the integrated discounted utility of consumption, after making allowance for the disutility associated with climate change. Whereas MERGE includes both market and non-market damages, it focuses on the latter, as they are considered the largest. In particular, market and non-market damages are assumed to be linear and non-linear with temperature increases, respectively, and follow the type of assumptions made

[1] Most of them are essentially based on a comparison of future consumption trajectories in the expected utility framework as originally developed by Mirrlees and Stern (1972).

in DICE (Nordhaus 1994). Thus, the loss resulting from climate change, possibly even climatic catastrophe, is supposed to increase disproportionally (in this case again quadratically) if mankind passes beyond an average atmospheric temperature increase of a few °C. While different numerical assumptions are made for different regions in the world, Manne and Richels (2004) presume that for a ΔT of 2.5°C an economic loss of 2% of GDP is incurred in high-income countries (in other words, the willingness-to-pay to avoid such a temperature increase is 2% of GDP).[2] At the basis of simulations performed with models like FUND and PAGE, and of the other modeling exercises referred to below (Cline 1992; Fankhauser 1995; Titus 1992), are damage cost assumptions similar to those made in DICE and MERGE, in some cases detailed per sector and/or region.[3] The parameter choices and the resulting damage costs, however, often vary substantially (see Table 1 in the next section).

Two recent studies have produced an overview of an important part of the climate change damage literature and made a comparison of two modeling exercises determining the marginal damage cost of CO_2 and its uncertainties (DEFRA 2004, 2005). They report central estimates for six points in time from 2000 to 2050. As an indication of the uncertainties they show a set of lower and upper central estimates as well as a lower and an upper bound (corresponding to 5% and 95% confidence intervals). We quote some of their results, using an exchange rate conversion of 1.5 €/£, to allow for later comparison. Their central estimate is 23 €/tCO_2 in 2000, increasing to 59 €/tCO_2 in 2050. The reported lower and upper central estimates for 2000 are 14 €/tCO_2 and 53 €/tCO_2, respectively. The lower bound is 4 €/tCO_2 (5% bound of PAGE) and the upper bound 90 €/tCO_2 (average of the 95% bounds of FUND and PAGE). Even though the range from lower to upper bound is enormous, it does not fully capture all published estimates. Indeed, even some negative values for the damage cost have been reported (implying net climate change benefits rather than costs) as well as values a couple of times higher than the upper bound. Tol (2005) also reviews a large number of climate change impact studies, and combines over 100 estimates for the marginal damage cost of CO_2 to form an overall probability density function. The uncertainty distribution is strongly right-skewed, with a median of \$3.8/tCO_2, a mean of \$25.4/tCO_2, and a 95% CL of \$95/tCO_2. According to Tol (2005), under standard assumptions of time discounting, equity weighting, and risk aversion, the marginal damage cost is unlikely to exceed \$14/tCO_2, and is probably smaller. This value is significantly lower than the \$85/tCO_2 reported by the widely publicized Stern Review (Stern et al. 2006), on which we will comment in the conclusion.

[2]For low-income countries, like China and India, the 'hockey-stick'-parameter they use in MERGE is smaller than 1. This means that at a per capita annual income between \$5,000 and \$50,000 a region is only willing to pay 1% of GDP to avoid a 2.5°C temperature rise, and at \$5,000 or below basically nothing. Above \$50,000 the 2% of GDP willingness-to-pay applies.

[3]Differences may exist though in assumptions on the tolerable temperature rise, defined as the ΔT below which no climate change damage is expected. While most models suppose a tolerable temperature of 0°C, Manne and Richels (2004) assume it to be the temperature level in 2000 (which was about 0.7°C higher than the average pre-industrial value) and Plambeck and Hope (1996) 2°C.

Table 1 Parameter values for ρ and corresponding ΔT_{cat} as assumed in several widely employed integrated assessment models of climate change

Source	ρ	ΔT_{cat} (°C)
Cline (1992)	0.014	20.7
Fankhauser (1995)	0.018	19.0
Manne and Richels (2004)	0.020	17.7
Nordhaus (1991, 1994)	0.009	26.0
Plambeck and Hope (1996)	0.018	19.0
Titus (1992)	0.013	21.9
Tol (1995)	0.020	17.7

N.B. Most of these authors report damages relative to GDP in the USA for one temperature increase level only, typically as associated with a doubling of the atmospheric CO_2 concentration. Roughgarden and Schneider (1999) apply Nordhaus' assumptions to the figures adopted by these authors in order to obtain expressions for the damage function of Eq. 2 consistent with DICE.

2.2 Damage cost as function of emissions

Following most of the integrated assessment studies (see references in Table 1), we use a damage cost function with the shape:

$$c_{dam/G} = \rho\left(\Delta T/2.5°\right)^{\theta} \tag{2}$$

in which $c_{dam/G}$ is the damage cost expressed as fractional loss of gross world product G, ΔT the global average temperature change with respect to the pre-industrial atmospheric temperature, and ρ and θ are coefficients (the factor 2.5°, often cited as the temperature rise for a doubling of CO_2, is convenient to render ρ dimensionless). For the current G we take a value of 50 trillion €/year.

Uncertainties about the coefficients ρ and θ abound. The function of Eq. 2 is usually assumed to be quadratic, so that θ is 2. Roughgarden and Schneider (1999) investigate values of θ other than 2 (both $1 < \theta < 2$ and $\theta > 2$) on the basis of a set of expert views. They conclude, however, that a quadratic damage function is most plausible: while $\theta = 2$ is not a necessity—the damage function may e.g. be somewhere in between linear and quadratic or perhaps even cubic—differences of opinion on climate damage costs show up primarily in the coefficient ρ of the damage function, rather than in its exponent. Roughgarden and Schneider (1999) argue that allowing for views from experts of different scientific disciplines—who have differing opinions on especially the likelihood of extreme climate events—implies variations of ρ by as much as an order of magnitude, but in most of the literature one finds values for ρ that typically lie between 0.006 and 0.025. Table 1 summarizes the values of the coefficient ρ as obtained from a survey of some of the most widely used integrated assessment models of climate change.

Formulated slightly differently, Manne and Richels (2004) assume in MERGE the relation:

$$c_{dam/G} = \left(\frac{\Delta T_{stab}}{\Delta T_{cat}}\right)^2 \tag{3}$$

in which ΔT_{cat} is the catastrophic temperature change at which all economic activity, hence the entire world product, is supposed to be wiped out. Combining Eqs. 2 and 3 one finds the ΔT_{cat} implicit in the models behind the references listed in Table 1.

In view of the above we assume that the damage cost $c_{dam}(t)$ in year t is related to the global average temperature rise $\Delta T(t)$ by

$$c_{dam}(t) = G(t)\,\rho\left(\frac{\Delta T(t)}{2.5^\circ}\right)^2 \tag{4}$$

where $G(t)$ is the annual gross world product. To calculate $\Delta T(t)$ we use the two-box model of Schneider and Thompson (1981) as described by Hammitt (1999). The increase in annual mean surface temperature $\Delta T(t)$ is obtained by solving the following coupled differential equations

$$\frac{d\Delta T(t)}{dt} = \left[Q(t) - \lambda\Delta T(t) - \frac{R_d}{\tau_d}\left[\Delta T(t) - \Delta T_d(t)\right]\right] \Big/ R$$

and

$$\frac{d\Delta T_d(t)}{dt} = \left[\Delta T(t) - \Delta T_d(t)\right]/\tau_d \tag{5}$$

where $\Delta T(t)$ and $\Delta T_d(t)$ are the temperature increases of the atmosphere/land/ocean-mixed layer and of the deep-ocean boxes (relative to their values in 1990), respectively; $Q(t) = 6.3\ln(p(t)/p_0)$ W/m^2 is the radiative forcing due to a concentration $p(t)$ of atmospheric CO_2 (with $p_0 = 280$ ppmv being the preindustrial value); $\lambda = 6.3\ln(2)/\Delta T_{2x}$ $W/^\circ Cm^2$ is the climate-feedback factor, with climate sensitivity ΔT_{2x}, the equilibrium increase in ΔT for a doubling of pre-industrial CO_2; $R = 20.83$ and $R_d = 223.7$ Wyear/°Cm^2 are the thermal inertia of the mixed-layer and deep-ocean boxes; and $\tau_d = 500$ years is a parameter describing the rate of heat transfer between the mixed layer and deep ocean.

Inserting the concentrations of the WRE scenarios of Wigley et al. (1996), shown in Fig. 1b, these equations can readily be solved by finite differences with a time step of 1 year. The resulting atmospheric temperature rise $\Delta T(t)$ for the WRE scenarios is plotted in Fig. 2.

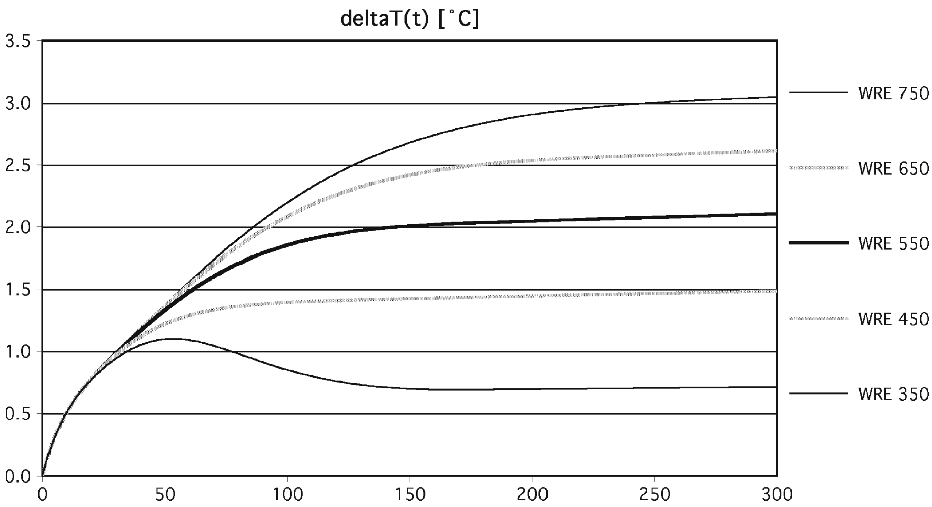

Fig. 2 The temperature rise $\Delta T(t)$ for the WRE scenarios

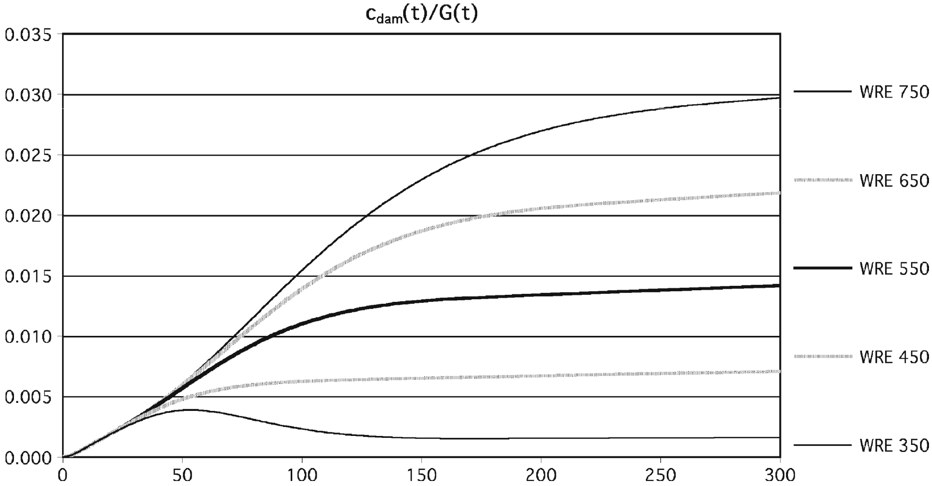

Fig. 3 The annual damage cost $c_{dam}(t)$, according to Eq. 4 with $\rho = 0.02$, shown as fraction of annual gross world product $G(t)$

Figure 3 shows the corresponding annual damage cost $c_{dam}(t)$ as fraction of annual gross world product $G(t)$, according to Eq. 4 with $\rho = 0.02$.

2.3 Abatement cost as function of emissions

Like in Rabl et al. (2005), we assume that the marginal CO_2 abatement cost, takes the functional form

$$c_{ab/ton} = \alpha \left(\frac{E - \beta}{E_s} \right)^{\gamma} \tag{6}$$

in which α(in €/tCO_2), β(in GtCO_2/year) and γ are coefficients characterizing the non-linear convex form of the abatement cost function; $c_{ab/ton}$ is the cost per ton of abated CO_2 at a global emission level E, given a starting emission level E_s. We choose the signs in Eq. 6 so that $c_{ab/ton}$ is positive for a reduction of E. The parameters α, β, and γ may be determined by least squares regression if cost data are available as a function of the abatement level. Alternatively, they may be estimated on the basis of energy technology assessments or energy systems modeling.

Here we choose the marginal abatement cost curves depicted in Fig. 4, based on an evaluation of published integrated assessment modeling results (see notably Goulder and Mathai 2000; Goulder and Schneider 1999; van der Zwaan et al. 2002; Yohe 1996).[4] Figure 4 contrasts with near-term abatement cost curves obtained through detailed engineering energy technology analyses, like with the GAINS model up to 2020 (Klaassen et al. 2005). Over such a short time frame the potential for deep reductions is limited or exceedingly costly, because many of the technological options available require long installation lead times or have costs that are unacceptably

[4]These references typically report shadow carbon prices, which we associate with the efforts needed to achieve carbon emission reductions or, alternatively, carbon abatement costs.

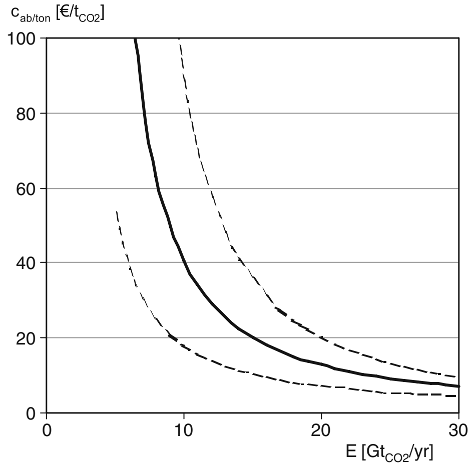

Fig. 4 Our choice for the marginal abatement cost curve (*solid line*) and lower and upper bounds (*dashed lines*). The coefficients are $\alpha = 7.5$, $\beta = 3$, and $\gamma = -1.3$ for the central curve, $\alpha = 5$, $\beta = 2$, and $\gamma = -1.1$ for the lower limit, and $\alpha = 10$, $\beta = 4$, and $\gamma = -1.5$ for the upper limit

high at the present time. In the long run, however, major cost reductions are to be expected as a result of technological progress and learning-by-doing. Thus, our abatement cost assumptions concern the long run and should not be interpreted as realistic short-term policy goals.[5] Note, however, that our model does not represent the phenomenon of learning, as a function of time or cumulative installed capacity, explicitly.

The total cost in year t of reducing CO_2 emissions from starting point $E_s(t)$ to level $E(t)$ is the integral of the marginal abatement cost of Eq. 6:

$$c_{ab}(t) = \frac{\alpha E_s(t)}{\gamma + 1}\left\lfloor \left(\frac{E_s(t) - \beta}{E_s(t)}\right)^{\gamma+1} - \left(\frac{E(t) - \beta}{E_s(t)}\right)^{\gamma+1} \right\rfloor \text{ for } \gamma \neq -1 \tag{7}$$

For $E(t)$ we take the emission scenarios of Fig. 1a, $E_s(t)$ being the reference scenario WRE750. We only consider values of $\gamma < -1$, since these provide a sufficiently broad abatement cost uncertainty range. Since Eq. 6 becomes meaningless for $E \leq \beta$, we assume an upper bound of 1,000 €/tCO_2 for the marginal abatement cost, corresponding to a technology that could be implemented without limit.

We have carried out a Monte Carlo analysis of Eq. 6, using the CrystalBall software and assuming that the parameters of the abatement cost curve are normally distributed, with the means and standard deviations Normal (7.5, 1.0) for α; Normal (3, 0.5) for β, and Normal (-1.3, 0.1) for γ. The resulting distribution of marginal abatement costs is approximately normal, except when the emission level drops below about 8 GtCO_2/year. The ratio of standard deviation and damage cost is about 0.15 at E = 25 GtCO_2/year, increasing to about 0.25 at E = 10 GtCO_2/year.

[5]Figure 4 shows marginal abatement costs only down to $E = 5$ GtCO_2/year, as below this reduction level they become much higher than marginal damage costs, such that effectively no mitigation takes place. Also, below this abatement level the cost uncertainties are too extreme to be of real significance.

3 Cost–benefit analysis: solution

The present value of the total life cycle costs for carbon abatement and for climate damage is calculated as the sum of annual costs $c_{dam}(t)$ and $c_{ab}(t)$, respectively, over a time horizon of N years, discounted at rate r_{dis}:

$$C_{ab,tot} = \sum_{i=1}^{N} c_{ab}(t)(1+r_{dis})^{-i} \quad \text{and} \quad C_{dam,tot} = \sum_{i=1}^{N} c_{dam}(t)(1+r_{dis})^{-i} \tag{8}$$

The damage cost $c_{dam}(t)$ of Eq. 4 contains the gross world product $G(t)$ which we assume to grow at rate r_{gro}. Carrying out these calculations we obtain five values of $C_{ab,tot}$ and $C_{dam,tot}$, corresponding to the five WRE scenarios. Since we want to interpolate between the scenarios, we now construct interpolating functions $C_{ab,tot}(E)$ and $C_{dam,tot}(E)$ where E is an emission label for the scenario. We choose to label and scale the scenarios by their emission level in year 300, that being almost their asymptotic level. To relate E to the corresponding asymptotic concentration p we show the latter versus E in Fig. 5, together with a linear fit; the equation for this fit is

$$p = 31.5\,E + 241.5\,\text{ppmv} \tag{9}$$

Now we are ready to optimize, i.e. to find the interpolated scenario with optimal emission E_o (in year 300) that minimizes the total life cycle cost in the sense of

$$\frac{d}{dE}(C_{ab,tot}(E) + C_{dam,tot}(E)) = 0 \quad \text{at} \quad E = E_o \tag{10}$$

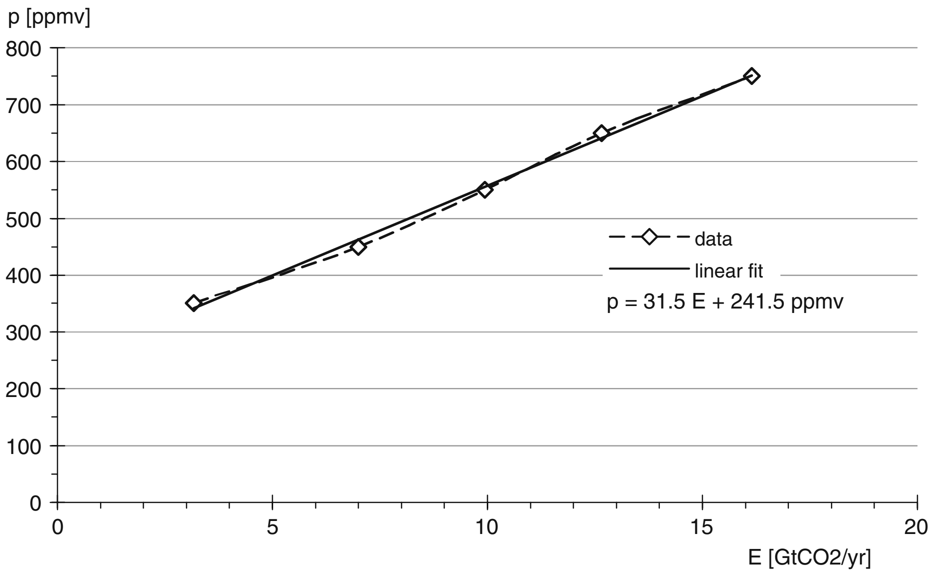

Fig. 5 Relation between stabilized concentrations p and emissions E in year 300 for the five WRE scenarios, together with a linear fit

Table 2 Central values and ranges of the parameters w for the damage and abatement costs in the optimization problem

Parameters w	w_{min}	$w_{central}$	w_{max}
Global			
N [years]	100	150	200
r_{dis}	0.01	0.02	0.03
r_{gro}	0.00	0.01	0.02
Damage cost $c_{dam}(t) = G(t)\,\rho\left(\frac{\Delta T(t)}{2.5°}\right)^2$			
ρ	0.01	0.02	0.03
Abatement cost $c_{ab}(t) = \frac{\alpha E_s(t)}{\gamma+1}\left[\left(\frac{E_s(t)-\beta}{E_s(t)}\right)^{\gamma+1} - \left(\frac{E(t)-\beta}{E_s(t)}\right)^{\gamma+1}\right]$			
α [€/tCO_2]	5.0	7.5	10
β [GtCO_2/year]	2	3	4
γ	−1.5	−1.3	−1.1

The uncertainties in ΔT are included in the uncertainty range of ρ

We use the NMinimize function of Mathematica® to obtain a numerical solution; all results in this paper are calculated with Mathematica.

Table 2 lists the central values, $w_{central}$, of all parameters of the optimization problem, as well as their ranges, $[w_{min}, w_{max}]$, considered for the uncertainty analysis in Fig. 7. For the central values of these parameters the optimal emission level is found to be $E_o = 8.0$ GtCO_2/year, less than a third of the current emission level of about 30 GtCO_2/year. Figure 6 shows the abatement, damage, and total costs expressed as fraction of total gross world product G_{tot} versus emission level E for

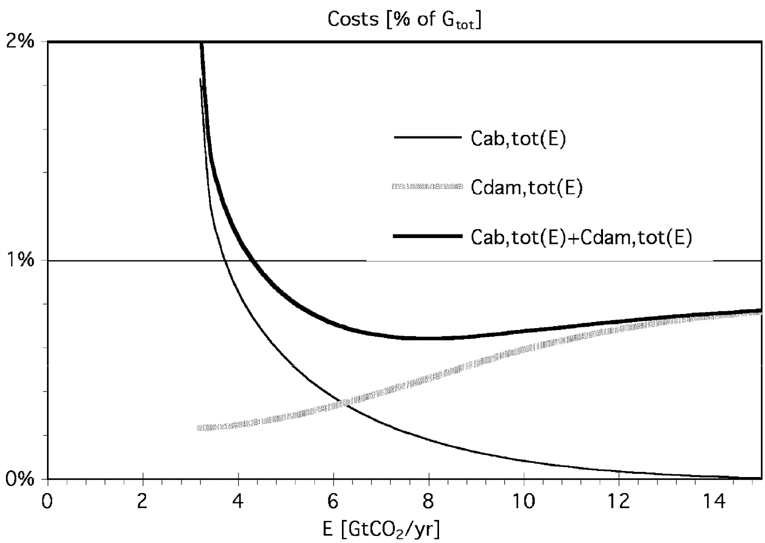

Fig. 6 Damage, abatement, and total costs expressed as fraction of total gross world product G_{tot} versus emissions level E for the central values of all optimization parameters

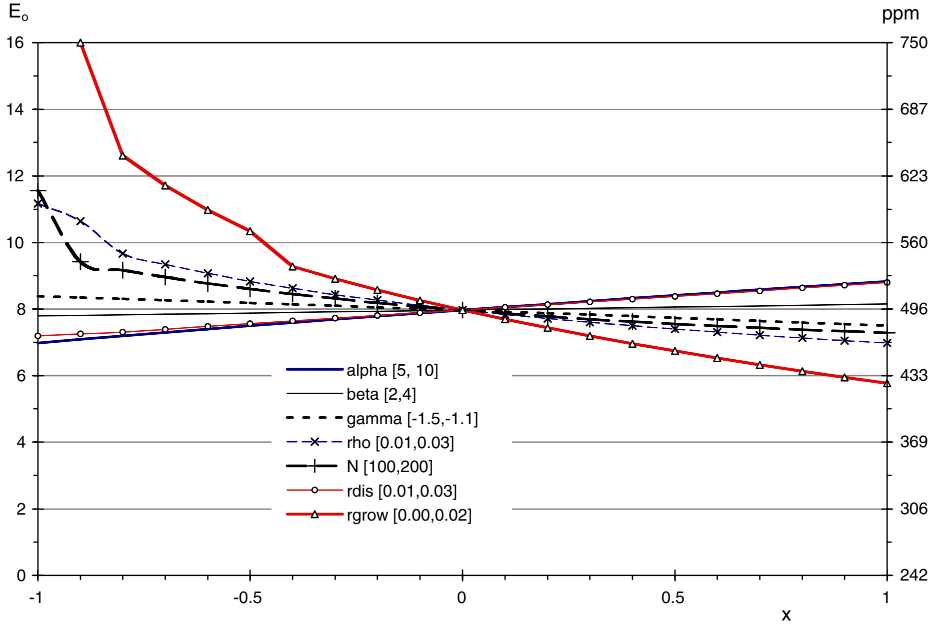

Fig. 7 Dependence of the optimal emissions level E_o [in $GtCO_2$/year] (*left hand scale*) on the parameters α, β, γ, r, r_{gro} and r_{dis}; *right hand scale* indicates the corresponding stabilized CO_2 concentrations. The uncertainties of ΔT are included in the uncertainty range of ρ. Each *curve* shows the effect of varying the parameter under consideration while keeping the others fixed at their central value. The x-axis shows the variation of each parameter w in non-dimensional form as $x = (2w - w_{max} - w_{min})/(w_{max} - w_{min})$

the central parameter values; G_{tot} is the sum of discounted values of annual gross world product $G(t)$ over N years

$$G_{tot} = G(1) \sum_{i=1}^{N} (1 + r_{gro})^i (1 + r_{dis})^{-i} \tag{11}$$

where r_{gro} is the growth rate of $G(t)$. For the central parameters $r_{dis} = 0.02\%$/year, $r_{gro} = 0.01\%$/year, and $N = 150$ years we have $G_{tot} = \$3.9 \times 10^{15}$.

The damage cost curve in Fig. 6 begins to level off beyond 10 $GtCO_2$/year instead of continuing to increase as it really should. The reason lies in the time limited horizon of our analysis. The choice of $N = 150$ years for Fig. 6 is clearly too short for the higher emission scenarios, as can be seen by looking at the emissions in Fig. 1a and the damage cost in Fig. 3. Since the higher emission scenarios reach their peak much later, ΔT and c_{dam} are still far below their asymptotic values after 150 years.

Even though this leveling off implies a significant underestimation of the damage cost for the high emission scenarios, it is not a problem for the optimization because E_o is sufficiently low, 8.0 $GtCO_2$/year, and even the uncertainty range in Fig. 7 is low enough not to be affected: for the scenarios WRE 350 to WRE 550 the damage cost at 150 years is sufficiently close to the asymptotic value. An alternative approach would be to extend the time horizon, but the time constant (of e.g. 500 years) of the model for ΔT (see Eq. 5) would be is so long that the corresponding estimation of costs would become more than dubious. Already the horizon of 150 years (and the uncertainty range, up to 200 years) is problematic, although anything much shorter would not be appropriate. Because of this underestimation of the damage for the high emission scenarios we do not take values of E_o above 12 $GtCO_2$/year seriously.

Figure 7 shows our results of our first uncertainty analysis. We vary each parameter w over the range $[w_{min}, w_{max}]$ as listed in Table 2, wide enough to span any reasonable possible value of w. To show results in a compact format we choose to represent w in non-dimensional form as $x = (2w - w_{max} - w_{min})/(w_{max} - w_{min})$. The central value $w_{central}$ equals $(w_{max} + w_{min})/2$, corresponding to $x = 0$. We do not consider the uncertainty of the ΔT calculation explicitly, but include it instead in the parameter ρ. For the large uncertainty range chosen for the parameters α, β, γ, ρ, $\mathrm{r_{gro}}$ and $\mathrm{r_{dis}}$, we find that E_o varies by less than 20% in most cases.

It may appear surprising that E_o and the corresponding stabilized concentration do not drop very low, staying above 6 $GtCO_2$/year and 433 ppmv for essentially all the points in Fig. 7. The reason lies in the very steep rise of the abatement cost curve as low emission levels are reached. Even if the damage costs were larger than the maximum considered in Fig. 7, the optimal level E_o would not decrease very much. Of course, Fig. 7 displays only the effect of varying a single parameter. To evaluate the uncertainty distribution when all parameters can vary over the ranges in Table 2 we have carried out a Monte Carlo calculation. The resulting distribution has a relatively heavy tail at high emissions, but that is unrealistic because the corresponding damages are underestimated as mentioned above. Not counting therefore the cases where E_o corresponds to the reference scenario WRE750 (i.e. no reduction at all), the standard deviation is about 2 $GtCO_2$/year. In the following section we take another approach and consider even larger uncertainties.

4 Cost penalty and value of research

The optimal emission level may well be determined incorrectly as a result of uncertainties in damage and abatement costs. Consequently, the real cost borne by society when establishing a desirable CO_2 emission level is larger than at the true optimum obtainable with perfect information. Of course, various political processes may also preclude the choice of the optimal emission level, but here we are interested in errors in E_o resulting from erroneously estimated damage and abatement costs. In particular, we examine by how much the total social cost increases above the optimum due to damage and abatement cost estimation errors. Rather than looking at the uncertainty in each of the parameters of Table 2 and Fig. 7, as we did in the previous section, we here take a simplified approach by considering overall errors in respectively the damage and abatement cost.

Suppose that damage costs have been estimated as $C_{dam,est}(E)$, while the true damage cost is $C_{dam,true}(E)$. Likewise, we assume that the abatement cost has been guesstimated as $C_{ab,est}(E)$, whereas it is really $C_{ab,true}(E)$. The optimal emission level corresponding to the estimated costs is $E_{o,est}$, instead of the true optimum $E_{o,true}$. We represent damage and abatement cost uncertainties by random variables, x_{dam} and x_{ab}:

$$x_{dam} = C_{dam,true}(E) \big/ C_{dam,est}(E) \tag{12}$$

and

$$x_{ab} = C_{ab,true}(E) \big/ C_{ab,est}(E) \tag{13}$$

We look at variations of x_{dam} and x_{ab} separately because their magnitudes and probability distributions are fundamentally different. Uncertainties in the abatement cost are much smaller than those in the damage cost. Also, for the former a normal distribution seems most plausible. We therefore characterize the distribution of x_{ab} by a Gaussian with mean 1 and standard deviation σ_{ab}. Since for large σ_{ab} a significant portion of the Gaussian corresponds to negative values of x_{ab}, i.e. negative abatement costs, we truncate the Gaussian at zero and replace it by a normalized distribution that is proportional to the Gaussian at positive x_{ab}.

For uncertainties in the damage cost function we assume a lognormal distribution. A variable has a lognormal distribution if the distribution of the logarithm of the variable is Gaussian. The lognormal distribution is strongly skewed, with a long tail of high values with low probability. It is usually characterized in terms of its geometric mean μ_g and its geometric standard deviation σ_g. Its geometric mean μ_g is equal to the median. If a quantity with a lognormal distribution has a geometric mean μ_g and a geometric standard deviation σ_g, the probability is approximately 68% for the true value to be in the interval $[\mu_g/\sigma_g, \mu_g, \sigma_g]$ and 95% for it to be in the interval $[\mu_g/\sigma_g^2, \mu_g, \sigma_g^2]$. Thus the confidence intervals (CI) of the lognormal are multiplicative, in contrast to the additive ones of the Gaussian.[6]

The highly skewed distribution of damage cost estimates in the literature (DEFRA 2004 and Tol 2005) is fairly consistent with a lognormal function, even though a few studies claim negative damages. Indeed, global climate change probably produces both winners and losers, at least at moderate temperature increases, but we do not believe that the net world-wide damage cost could be negative for any increase of the atmospheric CO_2 concentration. As representation of the estimates found in the literature we therefore take a lognormal distribution, and choose for its parameters a median $\mu_g = \$3.8/tCO_2$ and upper limit $\mu_g\ \sigma_g^2 = \$95/tCO_2$ of the 95% CI, that is, $\sigma_g = 5$.[7] In view of the limitations of currently available studies—notably the fact that some of the most troubling potential impacts, such as a change in the thermohaline circulation, rapid non-linear ice-sheet disintegration, or methane release from permafrost melting, have not yet adequately or hardly at all been taken into account—we realize that the uncertainty range may well be larger than $\sigma_g = 5$.

Since we focus in this section on variations in x_{dam} and x_{ab}, we use these variables as arguments of the true optimal emission level $E_{o,true}(x_{dam}, x_{ab})$ as well as of the difference $\Delta C(x_{dam}, x_{ab})$ between the total cost at $E_{o,est}$ and that at $E_{o,true}$:

$$\begin{aligned}\Delta C(x_{dam}, x_{ab}) = &\left[C_{dam,\,true}(E_{o,est}) + C_{ab,\,true}(E_{o,\,est})\right] \\ &- \left[C_{dam,\,true}(E_{o,\,true}) + C_{ab,\,true}(E_{o,\,true})\right]\end{aligned} \tag{14}$$

$\Delta C(x_{dam}, x_{ab})$ is the cost penalty due to errors in the damage and abatement cost functions. The results in this section are complementary to those of Fig. 7. We here cover a wider range of uncertainties than considered there, but present less

[6]See Spadaro and Rabl (2007) for more information on the use of lognormal distributions for the uncertainty analysis of environmental damage costs.

[7]This median and the upper limit of the 95% confidence interval are from the review by Tol (2005).

detail about the specific role of individual parameters. Starting from the quantities $C_{dam,est}(E)$, $C_{ab,est}(E)$, and $E_{o,est}$ as calculated with the central values of the parameters in Table 2, we now assume that the true costs are obtained by multiplication by the factors x_{dam} and x_{ab} as per Eqs. 12 and 13. As can be seen from Eqs. 4 and 7, the variation of x_{dam} is equivalent to variations in ρ and ΔT^2, while the variation of x_{ab} is equivalent to a variation in α.

The variation of the true optimal emission level $E_{o,true}(x_{dam}, x_{ab})$ is plotted in Fig. 8, in part a) as function of x_{dam}, keeping $x_{ab} = 1$, and in part b) as function of

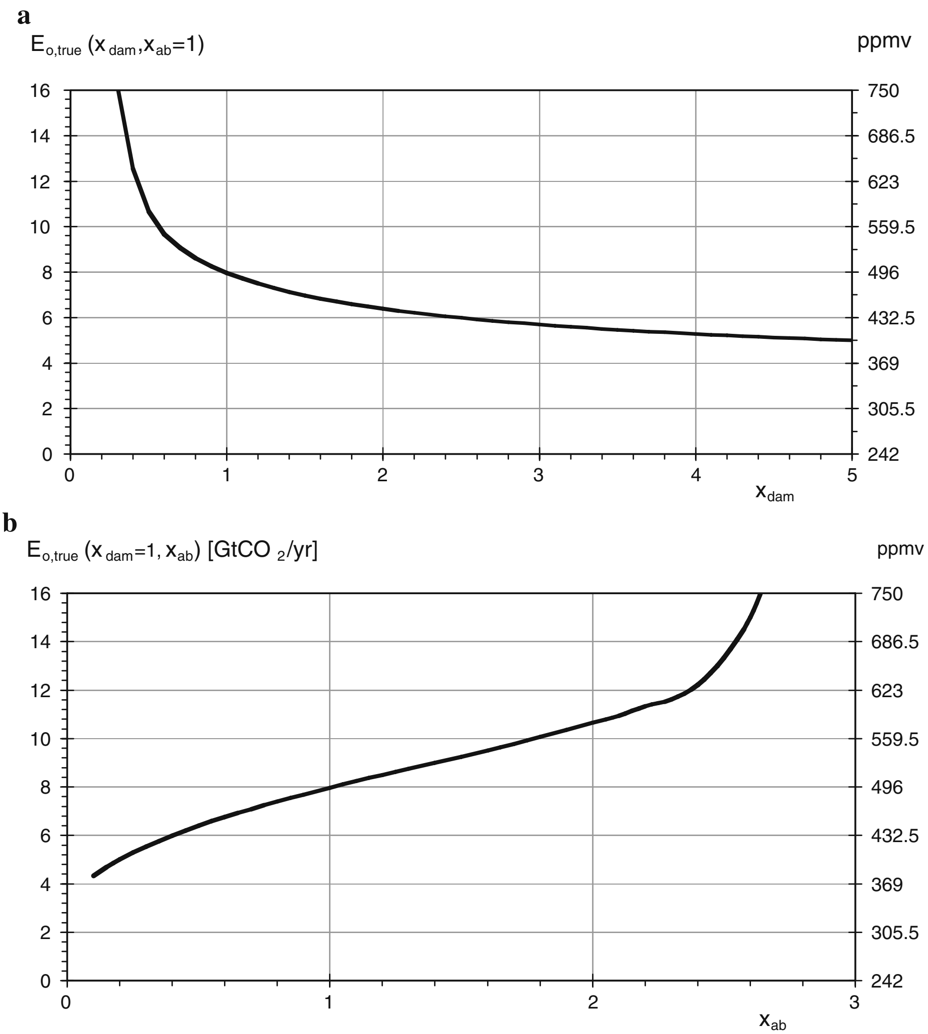

Fig. 8 Effect of uncertainties on the optimal emission level $E_{o,true}(x_{dam},x_{ab})$; the *right hand scale* indicates the corresponding stabilized CO_2 concentration. **a** True optimum if true damage cost is x_{dam} times larger than the estimate, keeping $x_{ab} = 1$. **b** True optimum if true abatement cost is x_{ab} times larger than the estimate, keeping $x_{dam} = 1$

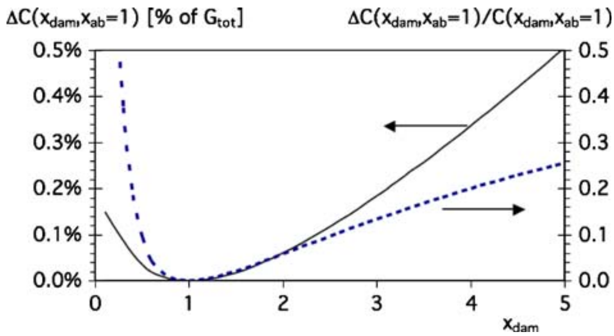

Fig. 9 The cost penalty $\Delta C(x_{dam},x_{ab} = 1)$ if the true damage cost is a factor x_{dam} times the damage cost estimate, as fraction of total gross world product G_{tot} (*solid line*, *left scale*) and as fraction of the total global warming cost $C(x_{dam},x_{ab} = 1)$ at the optimum (*dashed line*, *right scale*)

x_{ab}, keeping $x_{dam} = 1$. Since we think that the abatement cost uncertainty is smaller than the damage cost uncertainty, the depicted range of x_{ab} is smaller than that of x_{dam} (up to a maximum of 3 and 5, respectively). These plots display the same trends as Fig. 7, but cover wider ranges.

Figure 8 confirms our finding that optimal emission level E_o is within about 25% of the central estimate 8.0 $GtCO_2$/year for the plausible range of uncertainties. Levels above 10 $GtCO_2$/year are found only if the damage cost is very low and/or the abatement cost very high, cases that we do not consider seriously because of the above mentioned underestimation of the damage costs at high emissions. Compared to the reference scenario WRE 750 a deep cut in CO_2 emissions is clearly necessary.

The cost penalty $\Delta C(x_{dam}, x_{ab} = 1)$ resulting from damage cost errors is shown in Fig. 9 as function of x_{dam}, keeping $x_{ab} = 1$. To get a sense for the magnitude of the cost penalty with respect to the total costs incurred at the optimum, it is instructive to show the cost penalty both as fraction of total gross world product G_{tot} (solid line and left hand scale) and as fraction of the total global warming cost as ratio $\Delta C/C$ (dashed line and right hand scale), with in this case $\Delta C = \Delta C(x_{dam}, x_{ab} = 1)$ and $C = C(x_{dam}, x_{ab} = 1)$. Analogously, the cost penalty $\Delta C(x_{dam} = 1, x_{ab})$ due to abatement cost errors is shown in Fig. 10, in the same format. Like for Fig. 8, given that the uncertainty range for abatement costs is probably smaller than for damage costs, we think it justified to depict a smaller x-axis span for x_{ab} than for x_{dam}.

Like in Rabl et al. (2005), we find that the cost penalty is relatively small near the optimum, or, in other words, the optimum is fairly broad. The cost penalty becomes substantial only when the damage and abatement cost errors get large. Figure 9 shows that when the true damage cost is five times the estimated one, the cost penalty

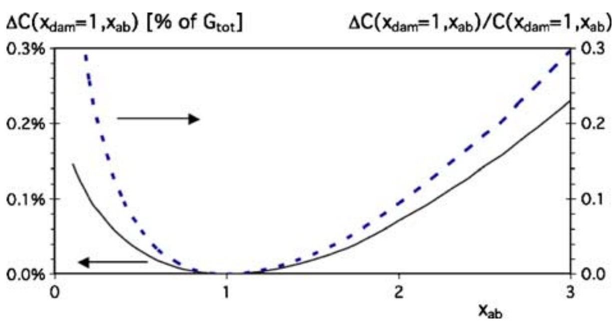

Fig. 10 The cost penalty $\Delta C(x_{dam} = 1,x_{ab})$ if the true abatement cost is a factor x_{ab} times the abatement cost estimate, as fraction of total gross world product G_{tot} (*solid line*, *left scale*) and as fraction of the total global warming cost $C(x_{dam} = 1,x_{ab} = 1)$ at the optimum (*dashed line*, *right scale*)

amounts to about 0.5% of the total gross word product G_{tot} (and 26% of the total global warming cost at the optimum). Figure 10 shows that when the true abatement cost is three times the estimated one, the cost penalty amounts to about 0.2% of G_{tot} (and 30% of the total global warming cost at the optimum). These percentages may still be considered modest, but in absolute terms the cost penalty can become enormous. The explanation is that the stakes involved in global climate change, i.e. the costs both at the damage and abatement side of the problem, are very high: 0.5% of G_{tot} is about \$20 trillion for our central assumptions ($r_{dis} = 0.02$, $r_{gro} = 0.01$ and $N = 150$ year).

Uncertainties in damage and abatement costs can be reduced by further research. To assess the value of such research we calculate the expectation value of the cost penalty $< \Delta C(x_{dam}, x_{ab} = 1 >$ (we use brackets $< >$ to designate expectation values) as function of the geometric standard deviation σ_{gdam} of the damage cost, with x_{dam} characterized by a distribution $Lognormal(1, \sigma_{gdam})$. Likewise, we determine the expectation value $< \Delta C(x_{dam}, =, x_{ab}) >$ as function of the standard deviation σ_{ab} of the abatement cost, with x_{ab} characterized by a distribution $Normal(1, \sigma_{ab})$. Even though abatement options exist with negative costs, we do not believe that on a global scale total long term abatement costs could be negative. We therefore truncate the normal distribution at $x_{ab} = 0$. The results are shown in Fig. 11.

Figure 11 provides an indication of the value of improved information on the damage and abatement costs. For example, if continued externality analysis reduces the geometric standard deviation of relative damage cost estimates from 5 to 4, the benefit is 0.05% of the total G_{tot} over 150 years (about \$3.9 × 10^{15}), and if further research reduces the standard deviation of relative abatement costs from 1 to 0.5, the benefit is 0.03% of G_{tot}. We thus conclude that research to reduce the uncertainty of damage and abatement cost estimates can be extremely cost-effective. We also

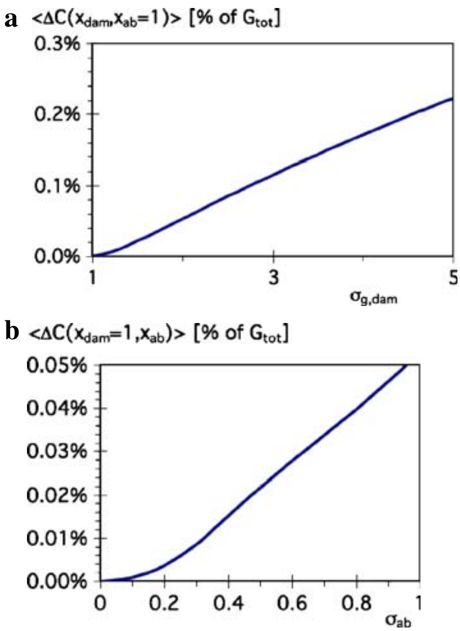

Fig. 11 Expectation value of the cost penalty. **a** $< \Delta C(x_{dam}, x_{ab} = 1 >$ as function of the geometric standard deviation $\sigma_{g,dam}$ of the damage cost; **b** $< \Delta C(x_{dam} = 1, x_{ab}) >$ as function of the standard deviation σ_{ab} of the abatement cost

observe that the possible gains from continued climate change damage cost analyses (i.e. climatic externality studies) may be significantly higher than those obtainable by increasing our understanding of the nature of abatement technologies and their prospected costs. The reason lies in the long tail of the lognormal distribution of the damage cost uncertainty, due to the possibility of extreme climate events with small likelihood but very high costs.

5 Conclusions and recommendations

We have carried out a cost–benefit analysis of climate change mitigation, with a focus on the uncertainties associated with both sides of the problem: the damage costs of CO_2 emissions and abatement costs of CO_2 emission reductions. To keep the analysis transparent we have introduced several major simplifications, especially by assuming emission scenarios that are scaled versions of the scenarios of Wigley et al. (1996). Thus we do not consider the optimization of the detailed time profile of the emissions. Based on a review of the literature, we have formulated elementary approximations for the damage and abatement cost functions. For the most plausible choice of the model parameters, we find that the optimum corresponds to an asymptotic emission level $E_o = 8.0$ $GtCO_2$/year, far lower than the current level of about 30 $GtCO_2$/year.

Varying the model parameters over a wide range, we evaluate the sensitivity of E_o and find that our central result is surprisingly robust. E_o changes by less than 25% for almost all of the plausible parameter ranges. Interestingly, our results imply that the optimal emission level is almost certainly not lower than $E_o = 6.0$ $GtCO_2$/year, i.e. about a fifth of current CO_2 emissions, the explanation for which is that the abatement costs become too high at this mitigation plateau.

Ultimately it is not only the optimal emission level and its uncertainty that matters, but the cost penalty, i.e. the extra social cost incurred due to an erroneously chosen E_o. Since the optimum is broad, the cost penalty is relatively small even for large errors in the estimation of relative damage and abatement costs. For example, if the true damage cost is five times the estimated one, the cost penalty amounts to about 0.5% of the total gross word product G_{tot} (and 26% of the total global warming cost at the optimum), and if the true abatement cost is three times the estimated one, the cost penalty amounts to about 0.2% of G_{tot} (and 30% of the total global warming cost at the optimum). Although these percentages are relatively small, even a fairly small relative error implies a large cost difference in absolute terms because of the enormous magnitude of G_{tot} (about \$3.9 $\times$ 10^{15} for our central parameter values $N_{year} = 150$ years, $r_{gro} = 0.01$ and $r_{dis} = 0.02$). We have therefore calculated the benefit of reducing these uncertainties. For example, if continued externality analysis reduces the geometric standard deviation of relative damage cost estimates from 5 to 4, the benefit is 0.05% of the total gross world product G_{tot} over 150 years, and if further research reduces the standard deviation of relative abatement costs from 1 to 0.5, the benefit is 0.03% of G_{tot}. Clearly, the value of information provided by increased climate change damage research can be enormous.

With $E_o = 8.0$ $GtCO_2$/year as optimal central emissions level and an uncertainty range of about 2.0 $GtCO_2$/year, we derive from Fig. 5 an optimal stabilized CO_2 concentration of $p_o = 496$ ppmv with an uncertainty range of about 60 ppmv.

This result is consistent with the recommendation of Stern et al. (2006) that the optimal climate stabilized concentration is around 500 ppmv CO_2 (equivalent) with an uncertainty range of about 50 ppmv. Of course, there are many differences in methodology between Stern et al. (2006) and the present paper. For instance, Stern et al. (2006) include all greenhouse gases (as CO_2 equivalent). But we strongly agree with the Stern review's overall conclusion that a deep cut in CO_2 emissions is required to avert the risk of excessive costs due to climate change.

From the above climate change cost–benefit analysis, and the description of the uncertainties involved, it is evident that much more work is required in the field of CO_2 damage and abatement cost calculations. Especially climate change damage research really has only barely started off. In order to reduce damage cost uncertainties and exploit the value of the corresponding information, it is particularly important to perform detailed analyses of regional climatic impacts and associated economic costs. These are needed to complement the highly aggregated studies produced so far, like the one presented in this paper. We thus agree with the recommendation by DEFRA (2004) that the disaggregation and valuation of damage costs by sector and region should be forcefully pursued. Determining the possible physical impacts of CO_2 emissions in all areas of economic and social activity should be vigorously continued, since the ensuing findings can effectively profit long-term policy making. The classical challenges of mitigation timing, social discounting, equity weighting, and risk aversion remain on the agenda, as well as the question how policy makers should confront the uncertainties associated with climate change damage and CO_2 abatement costs. To the latter, this article has attempted to contribute a step forward. As in the future more understanding on all the above fields emerges, the type of analysis presented here should be revisited. For the moment at least our study has shown how drastic the CO_2 emission reductions are that need to be reached.

Acknowledgements This work has been supported by the EC DG Research under the CASES (Cost Assessment for Sustainable Energy Systems) project of the ExternE series (Contract no. 518294) as well as the EXIOPOL (A New Environmental Accounting Framework Using Externality Data and Input-Output Tools for Policy Analysis) project. We would like to thank Erin Baker, Jae Edmonds, Geoffrey Heal, James Mirrlees, Jos Sijm, and Richard Tol, as well as the CASES project members, for providing us with their expertise, opinions, and suggestions. We also acknowledge the feedback given by many participants of the International Energy Workshop (IEW) 2008, held from 30 June–2 July in Paris (IEA), where this work was presented in the plenary session.

References

Baker E (2005) Uncertainty and learning in a strategic environment: global climate change. Resour Energy Econ 27:19–40

Cline WR (1992) The economics of global warming. Institute for International Economics, Washington DC

DEFRA (2004) The social costs of carbon (SCC) review—methodological approaches for using SCC estimates in policy assessment. Department for Environment, Food and Rural Affairs, London

DEFRA (2005) Social cost of carbon: a closer look at uncertainty. Department for Environment, Food and Rural Affairs, London

Fankhauser S (1995) Valuing climate change: the economics of the greenhouse. Earthscan, London

Goulder LH, Mathai K (2000) Optimal CO_2 abatement in the presence of induced technological change. J Environ Econ Manage 39:1–38

Goulder LH, Schneider SH (1999) Induced technological change and the attractiveness of CO_2 abatement policies. Resour Energy Econ 21:211–253

Hammitt JK (1999) Evaluation endpoints and climate policy: atmospheric stabilization, benefit–cost analysis, and near-term greenhouse-gas emissions. Clim Change 41:447–468
Heal G, Kriström B (2002) Uncertainty and climate change, working paper. Columbia Business School, New York
Keller K, Bolker BM, Bradford DF (2004) Uncertain climate thresholds and optimal economic growth. J Environ Econ Manage 48:723–741
Klaassen G, Berglund C, Wagner F (2005) The GAINS model for greenhouse gases, version 1.0: carbon dioxide, IIASA interim report IR-05-53. International Institute for Applied Systems Analysis, Laxenburg
Kolstad CD (1996) Learning and stock effects in environmental regulation: the case of greenhouse gas emissions. J Environ Econ Manage 31:1–18
Manne AS, Richels RG (2004) MERGE: an integrated assessment model for global climate change. www.stanford.edu/group/MERGE
Meehl GA et al (2007) Global climate projections, in climate change 2007: the physical science basis. In: Solomon S et al (eds) Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, pp 747–845
Mirrlees JA, Stern NH (1972) Fairly good plans. J Econ Theory 4(2):268–288
Nordhaus WD (1991) To slow or not to slow: the economics of the greenhouse effect. Econ J 101:920–937
Nordhaus WD (1994) Managing the global commons. MIT, Cambridge
Nordhaus WD, Popp D (1997) What is the value of scientific knowledge? An application to global warming using the PRICE model. Energy J 18(1):1–45
Peck SC, Teisberg TJ (1993) Global warming uncertainties and the value of information: an analysis using CETA. Resour Energy Econ 15(1):71–97
Plambeck EL, Hope CW (1996) PAGE-95: an updated valuation of the impacts of global warming. Energy Policy 24(9):783–794
Rabl A, Spadaro JV, van der Zwaan BCC (2005) Uncertainty of air pollution cost estimates: to what extent does it matter? Environ Sci Technol 39(2):399–408
Roughgarden T, Schneider SH (1999) Climate change policy: quantifying uncertainties for damages and optimal carbon taxes. Energy Policy 27:415–429
Schlenker W, Roberts MJ (2006) Nonlinear effects of weather on corn yields. Rev Agric Econ 28(3):391–398
Schneider SH, Thompson SL (1981) Atmospheric CO_2 and climate: importance of the transient response. J Geophys Res 86:3135–31470
Spadaro JV, Rabl A (2007) Estimating the uncertainty of damage costs of pollution: a simple transparent method and typical results. Environ Impact Asses Rev 28:166–183
Stern N et al (2006) The economics of climate change: the Stern review. Cambridge University Press, Cambridge
Titus JG (1992) The cost of climate change to the United States. In: Majumdar SK et al (eds) Global climate change: implications, challenges, and mitigation measures. Pennsylvania Academy of Science, Easton
Tol RSJ (1995) The damage costs of climate change: towards more comprehensive calculations. Environ Resour Econ 5:353–374
Tol RSJ (2005) The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties. Energy Policy 33(16):2064–2074
van der Zwaan BCC, Gerlagh R, Klaassen G, Schrattenholzer L (2002) Endogenous technological change in climate change modelling. Energy Econ 24:1
van der Zwaan BCC, Gerlagh R (2006) Climate sensitivity uncertainty and the necessity to transform global energy supply. Energy 31(13):2235–2251
van der Zwaan BCC, Rabl A (2009) Uncertainties of external costs: how large are they and to what extent do they matter? In: Markandya A, Bigano A, Porchia R (eds) (2009) The social cost of electricity: scenarios and policy implications, Fondazione Eni Enrico Mattei, Mimeo, Milan, Italy
Weitzman ML (2009) On modeling and interpreting the economics of catastrophic climate change. Rev Econ Stat 91:1–19
Wigley TML, Richels RG, Edmonds JA (1996) Economic and environmental choices in the stabilization of atmospheric CO_2 concentrations. Nature 379(6562):240–243
Yohe G (1996) Exercises in hedging against extreme consequences of global change and the expected value of information. Glob Environ Change 6(2):87–100