Norwegian University of Life Sciences
School of Economics and Business

Global Biodiversity Costs of Climate Change. Improving the damage assessment of species loss in Integrated Assessment Models

Kevin R. Kaushal and Ståle Navrud

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Abstract:

Climate change will have a major impact on global biodiversity. However, these changes – and their economic value– is inadequately captured in the existing Integrated Assessment Models (IAMs). We provide improved damage cost estimates based on a recent biophysical assessment of impact on species loss from increased global mean temperature, and value transfer from a recent global Delphi Contingent Valuation (CV) study of households´ willingness-to-pay (WTP) to avoid species loss due to deforestation of the Amazon rainforest. This is implemented in the FUND (Climate Framework for Uncertainty, Negotiation and Distribution) IAM. The numerical simulations suggest that the global species loss is lower than the original FUND model predicted. However, the economic valuation of the species loss is larger, resulting in higher aggregate biodiversity damage cost. Moreover, depending on the assumed marginal utility of consumption in the regions and discount rate used, the global Social Cost of Carbon Dioxide (SC-CO_2) could be more than seven times higher than in the original FUND 3.9 IAM. This indicate that IAMs with incomplete assessment and valuation of species loss could greatly underestimate SC-CO_2; and thus lead to underinvestment in greenhouse gas mitigation measures.

Key words: Integrated Assessment Models; Climate change; Ecosystem services; Species loss, Social Costs of Carbon Dioxide

JEL classification: Q54

Addresses:

Kevin R. Kaushal, School of Economics and Business, Norwegian University of Life Sciences
E-mail: kevin.raj.kaushal@nmbu.no

Ståle Navrud, School of Economics and Business, Norwegian University of Life Sciences
E-mail: stale.navrud@nmbu.no

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1. Introduction

In the field of economics, Integrated Assessment Models (IAMs) are among the important decision support tools in climate policymaking. These models estimate the global economic costs of climate change, often presented in terms of Social Costs of Carbon (SCC) estimates, and hence should be as complete as possible in terms of coverage of damages. The impact on biodiversity and ecosystem services are, however, not included or only partially assessed in the existing models. According to the fifth Assessment Report (5AR) of the Intergovernmental Panel on Climate Change's (IPCC), climate change will have a large impact on global biodiversity and ecosystem services, and is a key reason for concern (O'Neill et al. 2017). Thus, in order for the IAMs to be as complete as possible, it is important to quantify and these losses and value the related global damage costs[1].

Brooks and Newbold (2014) propose an updated biodiversity value function for assessing economic damages in IAMs. They use new global estimates of species loss rates due to global warming to re-calibrate the species loss function, and propose a new ecosystem nonuse value function. The latter is calibrated from Contingent Valuation Method (CV) and other Stated Preference (SP) studies of household´ willingness-to-pay (WTP) to preserve tropical rainforests and to protect endangered species in the U.S (Kramer & Mercer 1997; Richardson & Loomis 2009). Relying on U.S: studies only, they implicitly assume US households´ ´ WTP to be representative of the global population.

Our paper extends Brooks and Newbold's (2014) analysis from looking at the US households´ WTP only, to address the WTP of households worldwide to avoid the global species loss due to climate change . We achieve this by applying the results from a recent Delphi CV study of European, North American (USA and Canada), Oceanic (Australia and New Zealand) and South-East Asian households´ WTP to avoid specific scenarios for future species loss in the Amazon Rainforest (Strand et al. 2017). For the physical loss of species, we develop and calibrate a new species loss function based on the meta-analysis by Urban (2015). In contrast to the original species loss function in FUND 3.9, our functional form captures the accelerating increase of species loss with rising global mean temperature. Finally, whereas Brooks and Newbold keep

[1] In the following, we will use the words "impacts" and "loss" to describe impacts in physical terms, and "(economic) damage cost" to describe the economic damage costs in monetary terms.

everything except species constant, we fully integrate this loss function into the FUND 3.9 IAM (Anthoff & Tol 2014a). We then run the model to estimate the global species loss, the ecosystem damage costs and the resulting updated global Social Cost of Carbon Dioxide (SC-CO_2).[2]

The motivation for this paper is Brooks and Newbold's (2014, p. 348) request for further economic research in order to improve the IAMs in terms of "better estimates of the nonuse of biodiversity values through additional research on people's willingness to pay for biodiversity protection is sorely needed". By using the Delphi Contingent Valuation (CV) study of households´ WTP to avoid further deforestation and species loss in the Amazon rainforest (Strand et al. 2017), we have now covered the welfare loss of more than 60% of the world's population, and about 70% of the global population outside of Latin America. For the regions that are not included in the Delphi CV study, we estimate the WTP by unit value transfer with income adjustment from the regions where we have WTP estimates. With an estimated one out of ten known species on the planet living in the Amazon rainforest (WWF 2017), it is immensely biodiverse. Hence, implementing these results in an IAM would provide a better estimate of the damage cost of climate change to the cultural ecosystem service of non-use values of biodiversity[3].

We show by updating the species loss function that the species loss is somewhat l compared to the current FUND 3.9 model. However, the updated WTP estimates results in higher global ecosystem service damage costs as a fraction of regional income. Moreover, the ecosystem service damage cost as a fraction of global damage costs are higher as well. This is true for all the regions, but ecosystem service damages do vary across regions. The updated estimation of global damages results in a higher global SC-CO_2 compared to FUND 3.9 model. Under realistic assumptions the new global SC-CO2 could be more than seven times higher than predicted by the original FUND 3.9 model.

The rest of the paper is structured as follows. Section 2 describes three different IAMs (DICE, PAGE and FUND), and how species loss and ecosystem damage costs are included in these models. Section 3 updates the species loss function and WTP estimates in FUND 3.9.Section

[2] Social Cost of Carbon Dioxide (SC-CO_2) is a measure, in dollars, of the long-term damage done by a ton of carbon dioxide (CO_2) emissions in a given year. (Mastrandrea 2009).

[3] The Delphi CV survey covers mostly the non-use values, as these distant beneficiaries from countries outside of South America have never visited the Amazon rainforest, (and thus had no use value in terms of e.g. recreational use of the forest).

4 implements this in FUND 3.9; and projects the species loss, ecosystem damage and the SC-CO_2 under different assumptions to test the sensitivity of the SC-CO_2 estimates. Finally, section 5 concludes and outlines avenues for further research in order to improve the reliability and validity of ecosystem service damage costs in IAMs, and thus also of the global SC-CO_2 estimates.

2. Biodiversity and ecosystem damage in IAMs

The climate response in IAMs is usually described as impacts on society with one or more climate damage cost functions for each specific region (Mastrandrea 2009). These damage functions are usually converted to monetary estimates of the impacts in terms of loss of Gross Domestic Product (GDP) as a function of increased mean global temperature. The main purpose of IAMs is to better understand the global economic costs of climate change, and thus the economic benefits of policy measures to mitigate these impacts on social and natural systems. Damages in IAMs are generally assumed to rise with increasing temperature, but the size and functional form of these damage functions vary across the models. The global coverage and long time horizon of these IAMs necessitate a set of simplified assumptions, and there is a wide variation in how climate change damages occur in the models. There are many IAMs, but only a subset of them try to estimate the global economic damage costs from climate change. The most prominent ones of these are FUND, DICE and PAGE (Mastrandrea 2009). In this section, we will take a closer look at how biodiversity and ecosystem service damage cost are treated in these three models.

2.1. DICE

In the DICE (Dynamic Integrated Climate Economy) model, a representative agent maximizes her expected discounted future utility by choosing the level of consumption, savings and investment in greenhouse gas abatement based on a global aggregated constant-return-to-scale Cobb-Douglas production function. The climate change damages felt by the agent is specified as a global aggregated function. This single global damage function is based on the climate change impact from a list of sectors dependent on the magnitude of temperature change. However, the contribution of impacts from different sectors to total damages are not clearly represented in the model. According to documentation, the damages are based on studies of impacts in the United States, which are then scaled for application to other regions. Moreover, the climate change damage estimation is to a large extent based on “rough estimates” and the authors acknowledge that the methodology is at a speculative stage (Nordhaus & Boyer 2000, p. 86). In DICE2007 climate change damages predicted to affect “human settlement and natural ecosystems” is estimated to be 5.7% of total damage costs from a 2.5 °C rise in global mean temperature (Brooks & Newbold 2014; Nordhaus & Boyer 2000).

2.2. PAGE

PAGE (Policy Analysis of the Greenhouse Effect) is designed to allow all the five IPCC reasons for concern to be included in an IAM (Hope 2006, p. 19). The five IPCC reasons for concern are: i) risks to unique and threatened ecosystems, ii) risks from extreme climate events, iii) distribution of impacts, iv) aggregate impacts, and v) risks from future large-scale discontinuities. The model includes mean temperature dependent damages functions separated in eight world regions by two main sectors, “market” and “nonmarket”. The damage function includes a specified adaptation in the economy due to climate change, with an increasing annual “tolerable” level of temperature change. Like DICE, the damages in the different world regions are estimated based on impact studies in United States (Mastrandrea 2009). The relationships between impacts in different sectors and overall damages are, however, not clearly described in the models documentation, and there is no detailed description available nor discussion about biodiversity and ecosystem damage cost or losses (Hope 2006; 2008). This makes it difficult to relate the proportion of total damages to ecosystem services or biodiversity impact, and thus challenging to assess how a modified ecosystem and biodiversity impact function would change the initial results.

2.3. FUND

FUND (Framework for Uncertainty, Negotiation, and Distribution) has the most disaggregated presentation of climate change damages among the three mentioned models. The damage functions are dependent on both the size and the rate of temperature increase, and the model includes both sector- and region-specific impacts. The different sectors’ exposure to climate change is assumed to be affected by socioeconomic changes, and parameters in the model are estimated based on either published documentation or expert judgment. We also find an explicit damage function for ecosystem impact of climate change. Anthoff and Tol (2014a) state that the ecosystem damage assessment is based on the "warm-glow" effect, which they describe as "Essentially, the value, which people are assumed to place on such impacts, are independent of any real change in ecosystems, of the location and time of the presumed change, *etcetera* – although the probability of detection of impacts by the "general public" is increasing in the rate of warming" (Anthoff & Tol 2014a, p. 15) . Thus, they assume that people are not able to express their utility from avoiding species loss in terms of their WTP from Contingent Valuation and other Stated Preference surveys. This is contrary to current evidence; see e.g. Johnston et al. (2017). The FUND 3.9 model's open-access availability, and the explicitly stated assumptions and documentation including, makes it more straightforward to examine and update the ecosystem damages of climate change than DICE and PAGE. Like Brooks and Newbold (2014), we will in the next section look closer at FUND 3.9 and its ecosystem sector[4].

3. Updating the ecosystem damages in FUND 3.9

The ecosystem damage function in FUND 3.9 is based on two components. The first component is the *biodiversity* component and it consists of a species loss function related to temperature change over time. The other is the *impact biodiversity* with an economic value function linked to the species loss function. We will in the following section present both these components and suggest a modified and updated versions of them, while keeping the same structure of the overall model.

3.1 Biodiversity component

The species loss function in FUND 3.9 is specified as

$$B_t = B_{(t-1)}\left(1 - \theta - \varphi \Delta T^2_{(t-1)}\right), \tag{1}$$

where B_t is the number of species in time t on a global scale, θ and φ are parameters estimated to respectively 0.003 and 1.6 (φ with a range from 0 to 3.2), and ΔT is the temperature change from year $(t-1)$ to t (in degrees Celsius). These parameters are described as expert guesses in FUND

[4] FUND 3.9 is written in Julia and is publically available at http://www.fund-model.org/versions

(Anthoff & Tol 2014a, p. 16), and the number of species is assumed to be constant at 14 000 000 species until the year 2000. Hence, we can describe the species richness in FUND 3.9 as a function of an initial constant species loss rate θ over time (which occurs independent of climate change damages), multiplied by the square of the year-to-year temperature change. As Brooks and Newbold (2014) argues, the simplicity of the function has both its limitation and advantages. It does not represent the heterogeneity of biodiversity in all its forms, but the function can be calibrated using available quantitative studies. Further, Brooks and Newbold suggest a new species loss function based on studies of potential impacts of climate change on species and extinction rates; see equation (2) below:

$$1 - L_t = \left(\frac{1-\theta-\varphi\Delta T^2}{1-\theta}\right)^t, \qquad (2)$$

where $1 - L_{(t)}$ is the fraction of remaining species by some future year t, ΔT is the hypothesized constant annual temperature increase up to year t, and φ is a parameter based on existing studies of species loss under different climate change scenario (Malcom et al. 2006; May et al. 1995; Thomas et al. 2004; Warren et al. 2011). The shortcomings with equation (2) is that it is not flexible, and can handle only one scenario for species loss at a time. Furthermore, existing literature suggests an accelerating increase in species loss with future temperature rise (Urban 2015), while equation (1) and (2) does not project that. Hence, to better capture the species loss projected by Urban, we present equation (3) for the species loss as a function of global mean temperature in year t:

$$1 - L_t = (1 + \theta + \kappa T_t + \varphi T_t^2). \qquad (3)$$

In addition to parameters above, we also introduce a parameter κ which we also calibrate according to new estimations. The prediction of species response to future climate change are highly uncertain, and several attempts have been made to estimate the species response, but with mixed results. We will therefor re-estimate the species loss function based on Urban (2015), who performed a meta-analysis of 131 published estimates of the number of species threatened by extinction. Among the studies in this meta analyses, we also find those Brooks and Newbold

(2014) base their estimates on. Urban (2015) reports the results from the meta-analysis of species extinction risk from climate change under four different scenarios, listed in table 1. The numbers are on a global scale, meaning that some regions will have higher extinctions risk than others. The meta-analysis estimates, in general, show a lower fraction of species threatened by extinction than models in Brooks and Newbold (2014) and FUND 3.9 do.

Table 1: Predicted species loss from climate change under four different global mean temperature increment scenarios; 0.8, 2. 3 and 4.3 °C (Urban 2015).

Global mean temperature rise:	0.8°C	2 °C	3 °C	4.3 °C
Species extinction:	2.8 %	5.2%	8.5 %	16%

Natural rates of species extinction (or the probability/risk of extinction), denominated as θ in FUND 3.9 and estimated from fossil records, are believed to be between 10^{-7} and 10^{-6} per species per year, and are typically assumed to be constant over geologic time (May et al. 1995). The current background extinction rate is estimated by May et al. (1995) to be approximately 10^{-3}. Pimm et al. (1995) estimates the value to be in the range of 2×10^{-4} to 2×10^{-5}. However, this value could also be close to 1.5×10^{-3} depending on the number of threatened species that were to become extinct in the next 100 years. If we assume the lower estimates in Urban (2015) to be our current rate of species loss, then $\theta = 2.8 \times 10^{-4}$ which is not unreasonable compared to estimates from Pimm et al. (1995).

The unknown parameters φ and κ, are calibrated according to the results from Urban (2015), with suggested values of $\kappa = 1.73 \times 10^{-2}$ and $\varphi = 4.4 \times 10^{-3}$. Additionally, we investigate the robustness of our findings by assuming different extreme values for the predicted species loss.

3.2 Impact biodiversity component

In the impact biodiversity component, Anthoff and Tol (2014a) defines the impact of climate change on ecosystems, biodiversity, species, landscape etc. as followed

$$E_{t,r} = \alpha P_{t,r} \frac{y_{t,r}/y_{t,r}^{b}}{1+y_{t,r}/y_{t,r}^{b}} \frac{\Delta T_t/\tau}{1+\Delta T_t/\tau}\left[1+\sigma\left(\frac{B_0-B_t}{B_t}\right)\right], \tag{4}$$

where E is the value of loss of ecosystems at time t in region r, α is a parameter value of US \$50 per person if per capita income equals the OECD average in 1990, y denotes per capita income, y^b is a parameter set to US \$30 000,[5] P denotes population size, τ a parameter equal to 0.025, ΔT_t denotes the change in temperature (in degree Celsius), σ is 0.05, B_0 is the initial number of species set to 14 million, and B_t is the number of species in year t. E can also be interpreted as the WTP to avoid the loss of global species to climate change (Brooks & Newbold 2014). As Brooks and Newbold (2014) point out, there are some fundamental difficulties with equation (4). The damages mainly depends on the annual temperature change and not the fraction of remaining species. Moreover, there are no damages if the year-to-year temperature change is zero, even if the species loss is positive. We will later show that the impact on the biodiversity component accounts for a large share of the damage cost in FUND 3.9. Hence, updating equation (4) would have a significant impact on the overall damage cost in the model.

A new valuation function is introduced by Brooks and Newbold (2014) with a very similar functional form to Sterner and Persson (2008) and Weitzman (2010)

$$WTP_t = y_t - \left[y_t^{1-\eta} + \beta(\eta-1)ln\left(1+\Delta B_t/B_t\right)\right]^{1/(1-\eta)}. \tag{5}$$

We make a few but important changes to this function, in order to make it a better fit with the 16 world regions in FUND 3.9; listed in table 2. We estimate the WTP per capita for all of the world regions in FUND 3.9 based on Strand et al. (2017)

$$WTP_{t,r} = y_{t,r} - \left[y_{t,r}^{(1-\eta_r)} + \beta_r(\eta_r-1)ln\left(1+\Delta B_t/B_t\right)\right]^{1/(1-\eta_r)}. \tag{6}$$

[5] Which is the OECD average per capita income in year 1990.

y denotes per capita income in year t in region r, ΔB_t is the difference between projected biodiversity level without climate-change in year t and the projected biodiversity level under business-as-usual (BAU) scenario, (B_t), [6] and β_r is a calibrated parameter in each region. Hence, equation (6) expresses the households' consumption of market goods and services proportional to income in every period, and biodiversity is characterized as goods for the consumers. η_r is interpreted as the elasticity of marginal utility of consumption in region r, the higher the value of η is the less we value a dollar more of consumption (Sterner & Persson 2008; Weitzman 2010). We set η= 2 for all the regions as a base value, which seems to be a reasonable value as it is frequently used assumed in climate change modeling (Scarborough 2010; Sterner & Persson 2008; Weitzman 2010). Moreover, we later look at different combination of η, since this value may vary a cross the different regions. Table 2 lists all the regions in FUND 3.9 (Anthoff & Tol 2014b).

Table 2: The 16 geographical regions in FUND 3.9 (Anthoff & Tol 2014b).

1. USA	USA	9. Central America	CAM
2. Canada	CAN	10. South America	SAM
3. Western Europe	WEU	11. South Asia	SAS
4. Japan and South Korea	JPK	12. Southeast Asia	SEA
5. Australia and New Zealand	ANZ	13. China plus	CHI
6. Eastern and Central Europe	EEU	14. North Africa	NAF
7. Former Soviet Union	FSU	15. Sub Saharan Africa	SSA
8. Middle East	MDE	16. Small Island States	SIS

In Strand et al. (2017) they ask over 200 environmental valuation experts from 37 countries on four continents to predict their own country´s WTP per household for Amazon forest protection, using the Delphi Contingent Valuation (CV) method. Their survey is based on results on Soares-Filho et al. (2006), which project that roughly 30% of the forest area and 23% of the mammal species may face extinction in 2050 under the business as usual scenario. The WTP estimates to avoid this species loss are presented in table 3.

[6] $\Delta B_t = (B_t^0 - B_t)$, where B_t^0 is projected biodiversity level without climate change in year t.

Table 3: Table contains list of: (i) geographical regions in FUND 3.9 (see table 2 for explanation of the abbreviations); (ii) weighted average of GDP per capita in each geographical region; (iii) weighted average of household size in each geographical region; (iv) the weighted average of annual WTP per household in the geographical region; (v) calibrated parameter (β_r) based on the data collected; and (vi) weighted average of WTP per household in the geographical regions by Anthoff and Tol (2014a). Data for (i)-(vi) are collected from Strand et al. (2017); Eurostat (2016); Nakono (2012); World World Bank (2017); and UN (2012). All US$ values are reported in 2012$ (see appendix A for inflation adjustment according to IMF).

The geographical regions in FUND 3.9 (See table 2)	Weighted average of GDP per capita in the regions (in 2012 US$)	Weighted average of the household size in the regions (in year 2012)	Weighted average of the annual WTP per household in the regions given eq. (6) (In 2012 US$)	Calibration of the region specific parameter (β_r) from eq. (6)	Weighted average of the annual WTP per household given eq. (4) (In 2012 US$)
USA	50 900	2.59	67.70	3.18×10^{-8}	71.29
CAN	52 200	2.55	90.20	4.42×10^{-8}	65.21
WEU	43 211	2.22	48.65	3.97×10^{-8}	53.15
JPK	40 436	2.43	45.52	3.96×10^{-8}	55.37
ANZ	62 240	2.43	41.62	1.37×10^{-8}	72.68
EEU	12 721	2.55	25.09	5.65×10^{-8}	2.24
FSU	10 094	2.72	19.91	1.98×10^{-8}	6.83
MDE	12 637	5.64	24.92	3.69×10^{-8}	3.44
CAM	8 300	3.94	30.41	1.83×10^{-7}	1.43
SAM	10 890	3.44	39.91	1.46×10^{-7}	1.68
SAS	1 404	4.13	20.95	3.76×10^{-6}	0.35
SEA	3 885	3.97	9.05	2.35×10^{-7}	0.80
CHI	6 386	3.04	23.40	6.21×10^{-7}	0.45
NAF	4 095	5.06	15.01	3.62×10^{-7}	0.81
SSA	1 766	4.59	7.00	3.65×10^{-7}	0.94
SIS	7 227	3.50	26.48	1.51×10^{-7}	1.79

The USD values in table 3 are listed in nominal units[7], and the regions are represented by a weighted average of the population in each country of their respective regions. GDP per capita, household size and WTP are collected and calculated using a combination of sources (Eurostat 2016; Nakono 2012; Strand et al. 2017; UN 2012; World Bank 2017), while β_r is calibrated according to equation (6).[8] Some of the regions where not represented in Strand et al. (2017), for example, FSU, MDE, CAM, SAM, NAF, SSA and SIS. These regions' WTP are unit value transferred with income adjustment from other regions with similar characteristics, using equation (7) (Navrud & Ready 2007).

[7] Before using the dollar values in FUND 3.9, we adjust all values to 1995 US $ according to the geographical regions, see appendix A.

[8] The damage cost are accumulated from per capita damages in FUND, so we adjust the values from per household to per capita.

$$V_p = V_s \left({}^{Y_p}\!/_{Y_s} \right)^{\varepsilon}, \tag{7}$$

where V_p is the unknown WTP in a region p, V_s is the known WTP in region s, Y_p and Y_s are the income levels per capita, in region p and s, respectively; and ε is the income elasticity of WTP. We have used ε =1 in this unit value transfer; based on the results from Strand et al. (2017). In the far right column in table 3, we use equation (4) to estimate the WTP per household to be used in FUND 3.9. Here we insert the values from table 3, and use the temperature change in year 2050 from FUND 3.9's own forecast, ΔT_{2050} = 0.033. As table 3 shows, FUND 3.9 frequently estimates a different WTP compared to the results from Strand et al. (2017). Especially, the estimates for non-OECD countries seems to be significantly lower than Strand et al. (2017). The likely reason is: i) that there is only one parameter α which differentiates the geographical regions in FUND 3.9 into two groups (OECD and non-OECD), while in equation (6) there is one unique parameter β_r for every geographical region; and ii) that the WTP in the regions are mainly expressed as per capita income as a fraction of OECD average (given all other values are fixed). We also find that for OECD countries ($y_{t,r} \geq y^b$) in equation (4), the WTP as a fraction of GDP per capita decreases with higher income. While for non-OECD countries ($y_{t,r} \leq y^b$), the WTP as a fraction of GDP per capita increases with lower income.

4. Model simulation

In the following section we implement the revised and updated species loss and ecosystem damage cost function and values presented in chapter 3 in FUND 3.9. We compare the different species loss projections, and run sensitivity analyses to check for robustness.

4.1 Predicted extinction risk from climate change

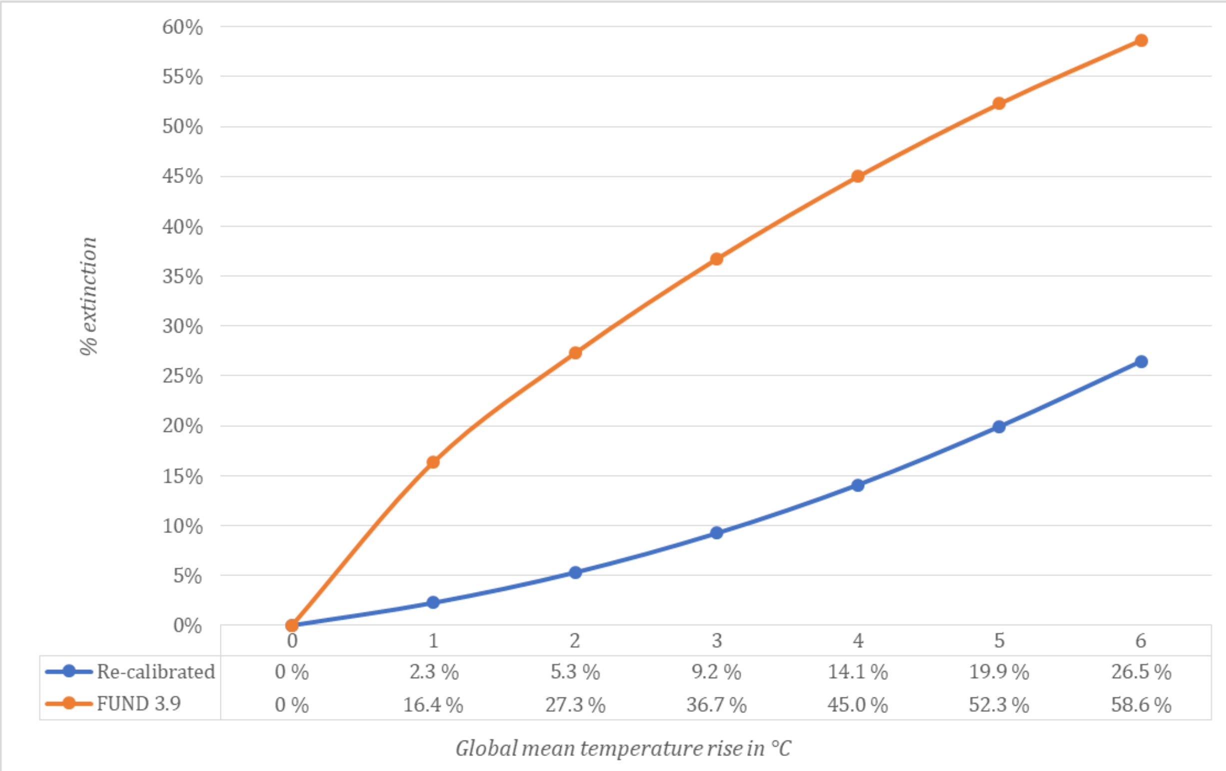

Figure 1: Projection of threatened species with rising global mean temperature, re-calibrated and the original FUND 3.9.

Existing literature suggests that species loss due to future climate change will not only increase but to accelerate as global temperatures rise (Urban 2015). In figure 1 we show the projected fraction of species threatened by global mean temperature rise, comparing the original FUND 3.9 with our re-calibrated model. Here we only look at the relative rise in global mean temperature and not at the time horizon, which we will come back to later in figure 2. The new projected loss is lower than what FUND 3.9 projects given temperature rise. The main reason is that the meta-analysis by Urban (2015) finds a lower projection of species loss with rising global mean temperature than what FUND 3.9 projects with equation (1). A central assumption when the time frame is presented, and was also pointed out earlier, is that the number of species is assumed to be constant until the year 2000 in FUND 3.9 (Anthoff & Tol 2014a, p. 16). So if the global mean temperature rises by 2°C, the global species loss increases to 5.3% in the re-calibrated model and 27.3% in FUND 3.9. This would happen in year 2074, or 74 years after the models assumes that the number of species are constant. If the Earth continues to warm up to 3°C, the extinction risk rises to 9.3% in our estimates compared to 36.7% according to FUND 3.9. Which is in 2097 according to the simulation. With 5°C global mean temperature rise, we estimate risk of losing 19.9% compared to 52.3% according to FUND 3.9, in year 2142. The new estimates are approximately the same as Urban (2015) finds in the meta-analysis. If we, however, in figure 1 assumes the preindustrial global mean temperature rather than year 2000 as our starting point, then we can see that we have already passed the 1°C mark in year 2015 (NASA 2016). So with this assumption, in year 2015 the predicted global species loss increased to 2.3% in our estimates compared to 16% according FUND 3.9. Thus, this underlines how important the assumptions are when projecting the global species loss.

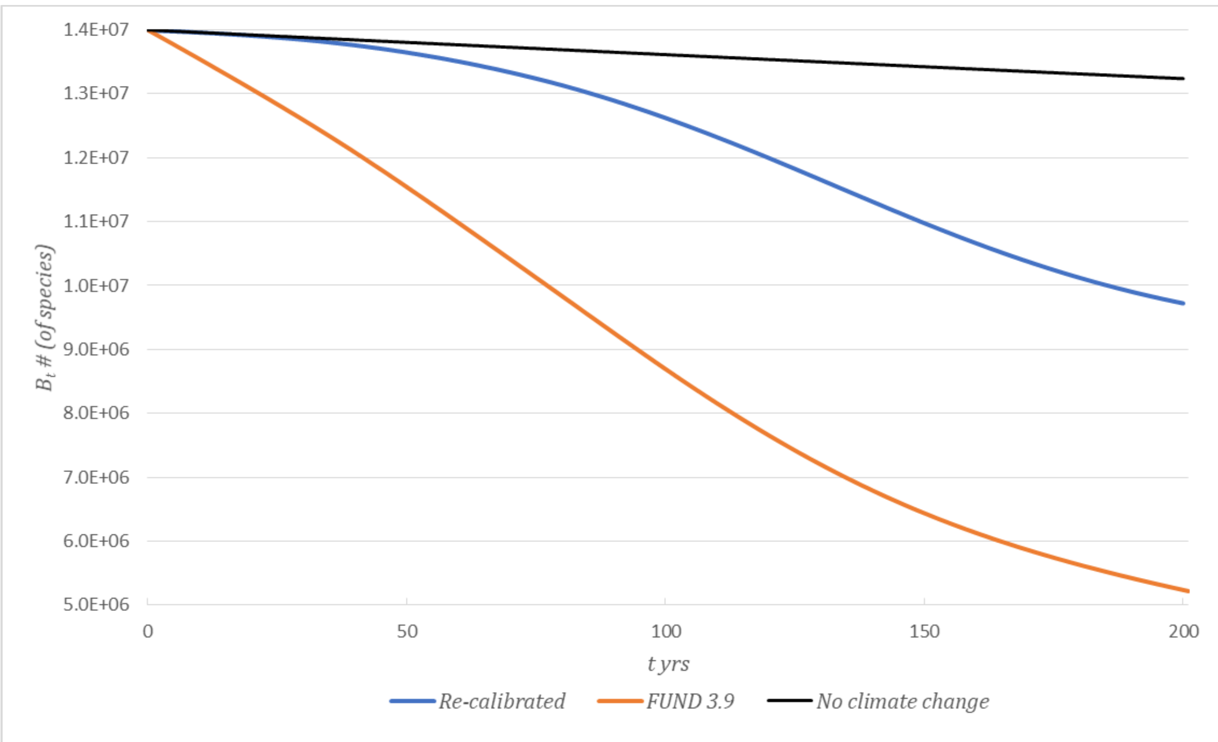

Figure 2: Projection of global species loss over time comparing scenario no climate change, re-calibrated model and FUND 3.9.

If we measure the number of species left in year t, figure 2 shows the comparison of our re-calibrated model with FUND 3.9 and assumption of no climate change. Here, the parameter assumption of no climate change is the same from our section 3 in equation (3), $\theta = 2.8 \times 10^{-4}$ each year. In year t =200, our estimated model projects approximately 70% remaining species compared to 37% according to FUND 3.9. Assuming that there are some species projected to go extinct with no climate change, these numbers are corrected to 74% and 40%, respectively. It is important to point out that the annual temperature change in FUND is not constant. This is why our curves in figure 2 are not linear like Brooks and Newbold (2014), who assumed a constant annual temperature change.

4.2 Projected ecosystem damages and the social cost of carbon dioxide

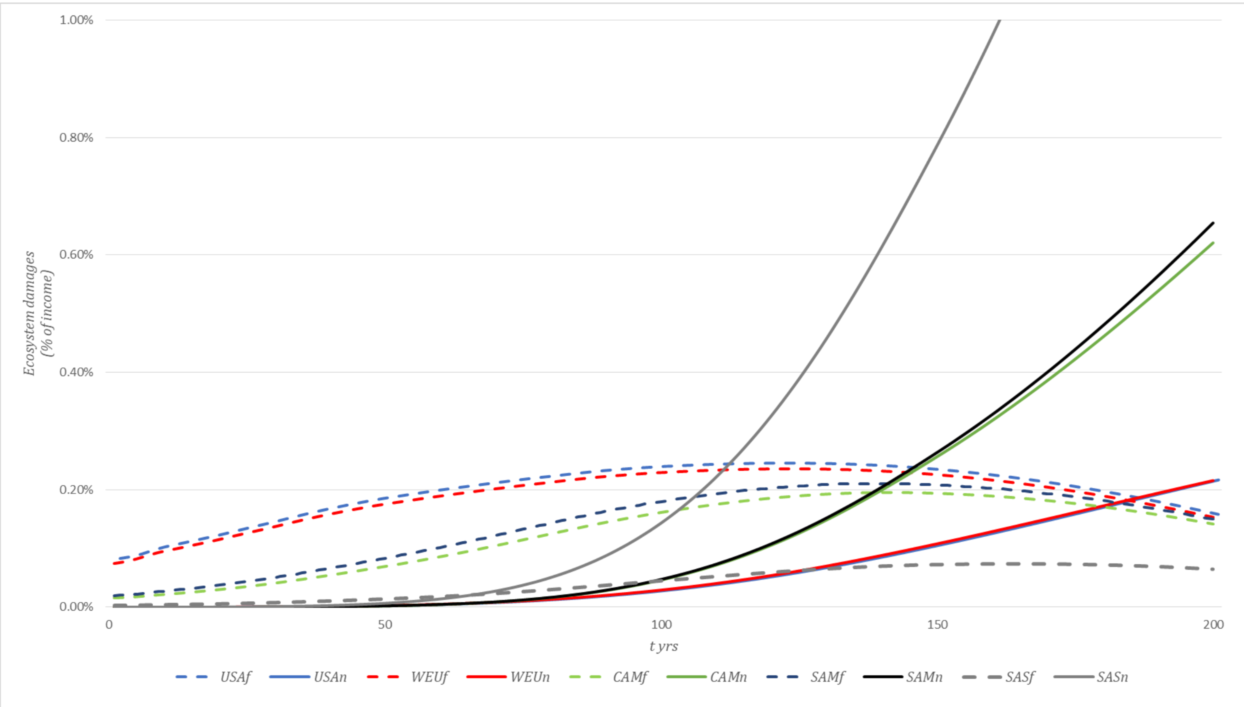

Figure 3: Projection of ecosystem damage cost as a fraction of income in different regions, using FUND 3.9 and re-calibrated model, with using the new loss function in equation (3). With *f* in the description, we combine equation (3) with the old valuation function in equation (4). With *n* in the description, we combine in equation (3) with the new valuation function in equation (6)

Figure 3 above shows the projection of ecosystem damage cost as a fraction of income, in selected regions. An *f* in the region description indicates that we have combined the new species loss function in equation (3), with the original damage function in FUND 3.9 in equation (4). With indicator *n* in the region description, we have combined the new species loss function in equation (3) with the new damage function in equation (6). The loss of species in the new valuation function are estimated using η=2, and the income is measured in GDP per capita. The new ecosystem valuation function in equation (6), projects the fraction of income to increase over time at an increasing rate. FUND 3.9 on the other hand projects that this fraction will increase with a decreasing rate over time. As stated in section 3, the original damage cost function in equation (4) is more dependent on the yearly temperature change rather than actually species loss. So with global mean temperature rise declining over time, the valuation in equation (4) predicts lower damages as a fraction of income. Thus, the concave form of FUND 3.9's prediction.

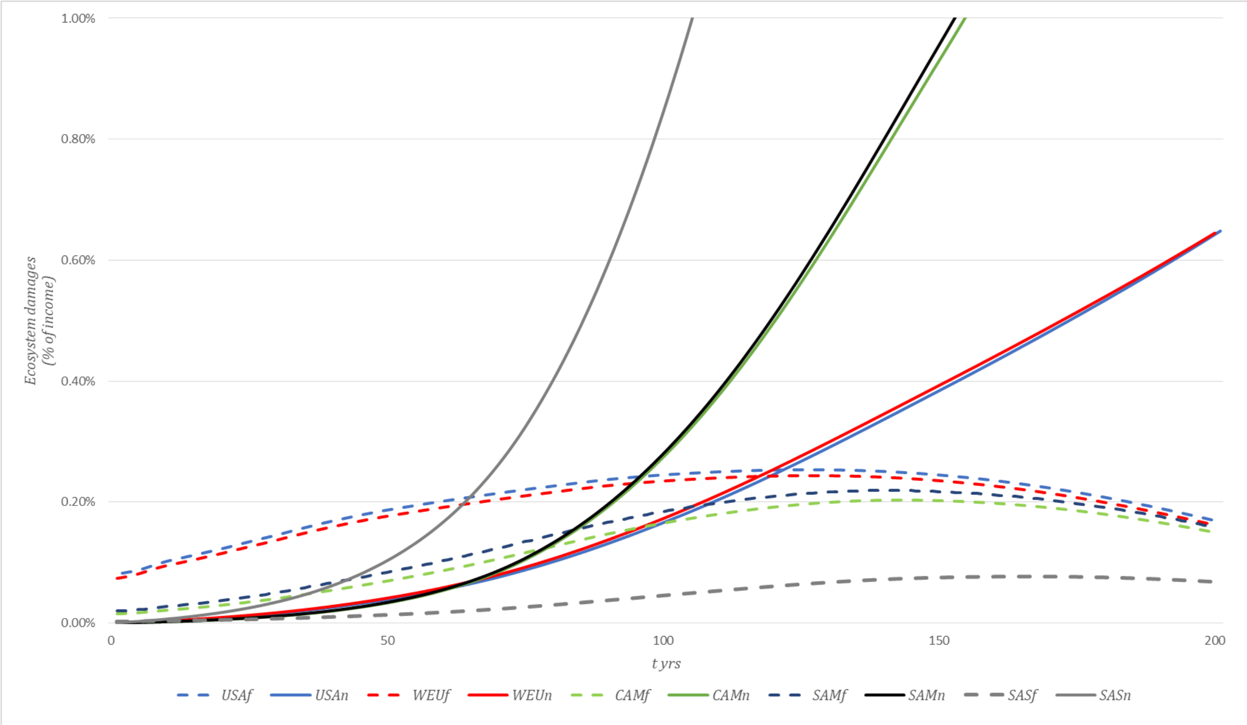

Figure 4: Projection of ecosystem damage cost as a fraction of income in different regions, using FUND 3.9 and re-calibrated model, with the old species loss function in (1). With *f* in the description, we combine equation (1) with the old damage cost function in equation (4). With *n* in the description, we combine the loss function in (1) with the new damage cost function in equation (6)

In figure 4, we show the projection of ecosystem damages as fraction of income given the old species loss function, according to equation (1). Hence, an *f* in the region description in figure 4 indicates that we have combined the old species loss function in equation (1), with the original damage cost function in FUND 3.9 in equation (4). With indicator *n* in the region description, we now have combined the old species loss function in equation (1) with the new damage cost function in equation (6). By comparing figures 3 and 4, we see that as the damages as a fraction of income increases more rapidly in figure 4 than in figure 3 with the new species loss function (3). FUND 3.9's damage cost on the other hand, does not seem to be very different even with higher species loss in equation (1). This yet again underlines the temperature change dependency rather than actual losses for the species loss function in (1).

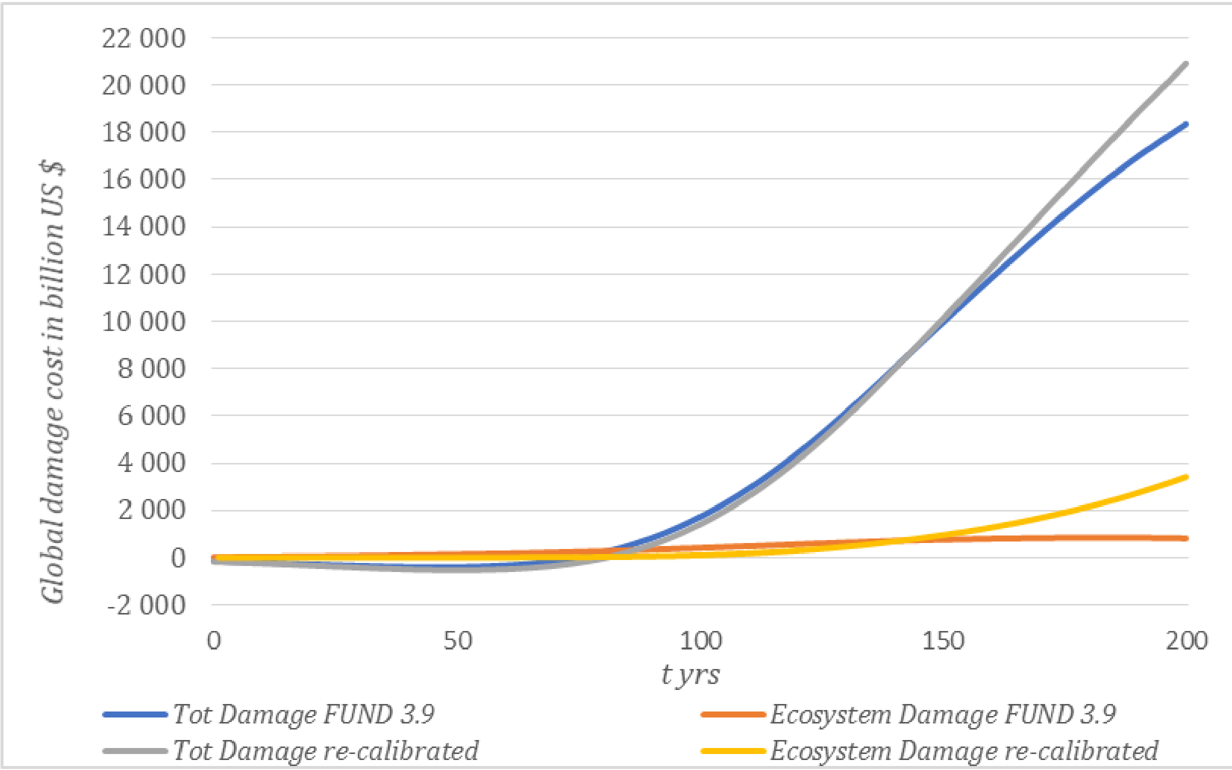

Figure 5: Projection of total damage cost and ecosystem damage cost over time, comparing FUND 3.9 and re-calibrated model. In 1995 US $.

The total global damage costs in FUND 3.9 is divided into *economic* damage cost and *non-economic* damage cost. [9] If we compare the global ecosystem damage cost with the total damage cost, figure 5 shows how our re-calibrated model compare with FUND 3.9. The ecosystem damage cost in FUND 3.9 is relatively flat over time, while in the re-calibrated model the damage cost increases with an accelerating speed. This affects the total damage costs, which increase more than in the original model. Compared with FUND 3.9, the re-calibrated ecosystem damage cost represents a bigger share of the total damage cost, and hence also the non-economic damage cost[10].

FUND also reports the global Social Cost of Carbon (SCC), which according to Anthoff et al. (2011) in FUND is defined as follows:

$$SCC_r = \left. \sum_{t=2010}^{3000} \frac{D_{t,r}(E_{1950} + \delta_{1950}, \ldots, E_t + \delta_t) - D_{t,r}(E_{1950}, \ldots, E_t)}{\prod_{s=2010}^{t} 1 + \rho} \middle/ \sum_{t=1950}^{3000} \delta_t \right.$$

[9] In Appendix A, we show a detailed list of *economic* and *non-economic* damage cost in FUND 3.9.
[10] The ecosystem damage cost as a fraction of non-economic damage cost is illustrated in figure A1, in appendix A.

$$(8)$$

where SCC_r is the social cost of greenhouse gas in region r (in 1995 US $ per ton), t and s denotes time (in years), D are impacts in US dollars per year, E are emissions of carbon, δ are incremental emissions[11] and ρ is the discount rate (Anthoff et al. 2011). From equation (8) we use the base case of global social cost of carbon:

$$gSCC = \sum_{r=1}^{16} \frac{Y_{2010,ref}}{Y_{2010,r}} SCC_r. \tag{9}$$

where $gSCC$ is the global social cost of carbon, $Y_{2010,ref}$ is the average per capita consumption in the reference region[12] in year 2010, and $Y_{2010,r}$ is the regional average per capita consumption in year 2010. The estimated global SCC in 2010 are reported in table 4 using FUND 3.9 and the new estimations. FUND 3.9 reports SCC in metric tons of carbon, while in this paper we use metric tons of carbon dioxide CO_2, i.e., Social Cost of Carbon Dioxide (SC-CO_2).[13]

Table 4: Estimated global Social Cost of Carbon Dioxide (SC-CO_2) in 2010. *New* lists the SC-CO_2 assuming new species loss (3) and damage cost function (6). *FUND 3.9* lists the original SC-CO_2 prediction by FUND 3.9. *New w/ (1)* lists the SC-CO_2 with old species loss (1) and new damage cost function (6). *FUND 3.9 w/ (3)* lists the SC-CO_2 assuming new species loss function (3) and old damage cost function (4). Discount rate ($\boldsymbol{\rho}$) is assumed 2% and 3%. All values listed in 1995 US $.

	New	**FUND 3.9**	**New w/ (1)**	**FUND 3.9 w/ (3)**
Global SC-CO_2 ($\rho \approx 2\%$)	$62.91	$27.80	$-7.84	$27.82
Global SC-CO_2 ($\rho \approx 3\%$)	$6.78	$6.55	$6.23	$6.55

Table 4 shows that the estimated global SC-CO_2 with $\rho \approx 2\%$ is US $62.91, with our re-calibrated model[14]. These projections are more than twice the size of what FUND 3.9 reports. Moreover, FUND 3.9's estimated global social cost of carbon is roughly the same even with less species loss. This is shown in the table with original FUND 3.9 and FUND 3.9 with re-calibrated species loss function (3). When we use the updated ecosystem damage cost and old species loss

[11] SCC_r, E, and δ are reported in metric tons per year.
[12] The reference region in FUND 3.9 is the world (Waldhoff et al. 2014)
[13] To convert from metric ton of CO_2 to metric ton of carbon, multiply by $\frac{12}{44}$ (Carbon Trust 2008)
[14] Roughly US $ 89.20; USA-inflation-adjusted to 2010 US $

function (*New w/ (1)*), table 5 shows a negative global SC-CO_2. The intuitive explanation is that the possibility for adaption is more difficult the more we value the ecosystem, thus leading to lower SC-CO_2 while the ecosystem damages are far greater. Evidently, the values are lower with $\rho \approx 3\%$, and the difference between FUND 3.9 and the updated model is not so large anymore. This is due to the fact that the growing ecosystem damages are greater in the far future, as shown in figure 3 and 4. A low discount rate, in particular, gives a greater weight to the longer-term impacts.

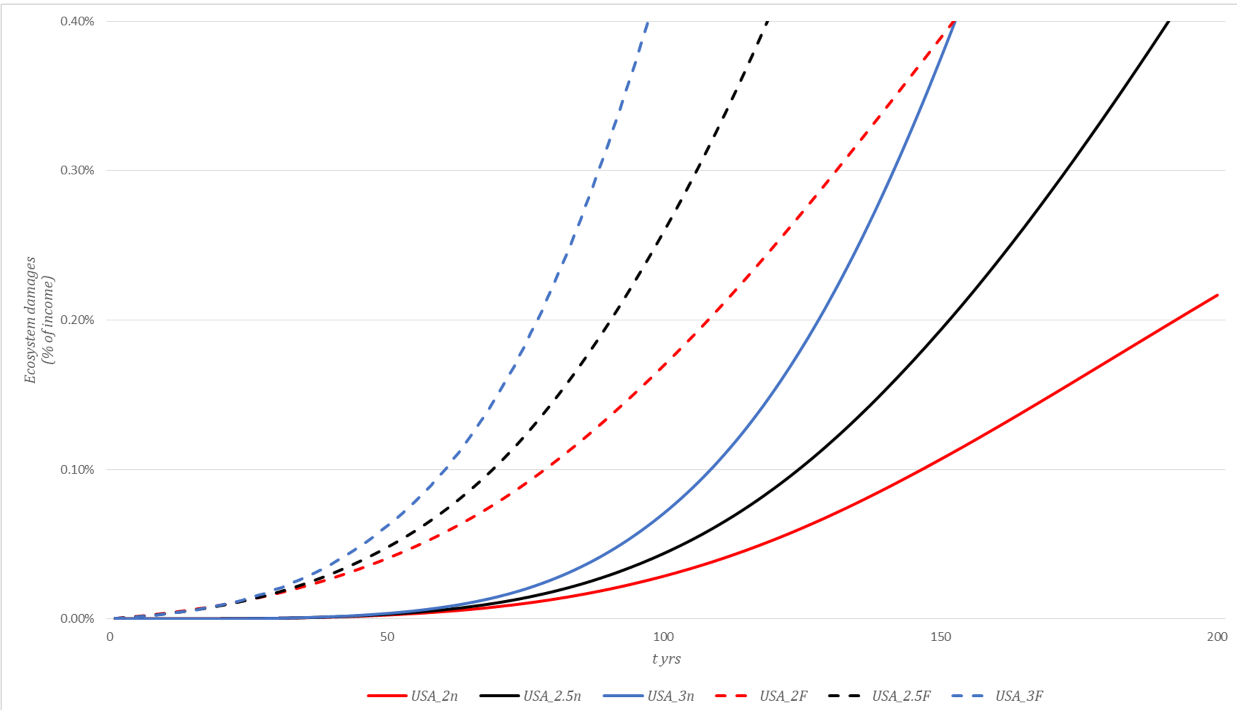

Figure 6: Projection of ecosystem damages as a fraction of income in USA, using different η and species loss functions. Numbers in description indicates the assumed *marginal utility of consumption* η values (2, 2.5 and 3). *N* is the new loss function (3) and *f* is the old loss function (1)

The correct value of elasticities of marginal utility of consumption η, is a topic for discussion. The value of 2 is not unreasonable, but it may vary across regions. Figure 6 underlines the importance of using a reasonable value for η by looking at the results in USA. *n* is the new species loss according to equation (3), *f* for species loss according to equation (1), and the numbers indicate the value of η. As figure 6 shows, a low (higher) η leads to a lower (higher) ecosystem damage cost as a fraction of income over time.

Table 5: Estimated global Social Cost of Carbon Dioxide (SC-CO_2 under different assumption of marginal utility of consumption η, in 1995 US $.

	η=2	η=3	η_{OECD} = 2 $\eta_{NON\text{-}OECD}$ =3	FUND 3.9
Global SC-CO_2 ($\rho \approx 2\%$)	$62.91	$201.22	$73.76	$27.82
Global SC-CO_2 ($\rho \approx 3\%$)	$6.78	$10.69	$9.64	$6.55

Table 5 lists the sensitivity of global SC-CO_2 with different η. With η =3 and $\rho \approx 2\%$, the global SC-CO_2 is more than three times the size of η =2, in our updated model. Moreover, if we assume a lower η in OECD countries than non-OECD, the estimated global SC-CO_2 is approximately $73.76. All of these values are higher than what FUND 3.9 originally estimates with $\rho \approx 2\%$ or $\rho \approx 3\%$.

5. Concluding remarks

We update and extend both the climate change induced species loss function and the economic valuation of this species loss in the Integrated Assessment Model (IAM) FUND 3.9, in order to better account for spatial heterogeneity in both species loss and households´ willingness-to-pay (WTP) to avoid this loss. We use results from a global Delphi Contingent Valuation (CV) study together with value transfer techniques to increase the global coverage and reliability of the damage cost estimates for species loss. Thus, we get a more comprehensive estimate of the social costs of carbon in terms of SC-CO_2. SC-CO_2 estimates are used as decision support and input to Benefit-Cost Analyses of climate change mitigation and adaptation measures; see e.g. Greenstone et al. (2013)

The new species loss function projects lower species loss than FUND 3.9. However, the improved economic valuation of the species loss results in higher damage costs for all geographical regions. Thus, the damage costs now increase more with rising global mean temperature, resulting in higher global damage costs. This in turn gives higher overall global SC-CO_2 estimates than in FUND 3.9. When testing for robustness in sensitivity analyses, the global SC-CO_2 estimates were consistently higher with the updated species loss and economic value functions.

Sensitivity analyses were also conducted in order to illustrate the uncertainty in the estimates at different stages of the damage cost function approach used here to calculate the SC-CO_2

estimate. The growing biodiversity damage costs are greater in the far future, and the magnitude of global SC-CO_2 is very sensitive to the assumptions used for the social discount rate and the elasticities of the marginal utility of consumption. Therefore, future analyses should look into these two factors, but also evaluate the current practice in FUND 3.9 (and other IAMs) of updating economic damages to current prices using US dollars and the US Consumer Price Index. Ideally, Purchase Power Parity (PPP) adjusted exchange rates should be used to convert damages in different regions to PPP-USD, and the regional CPIs (see Appendix A) should be used to update regional damage estimates to current values. For species loss this implies that households´ valuation of public goods like biodiversity increase at the same rate as the market prices of the basket of goods that underlies the CPI. However, people's valuation of species loss could deviate from the CPI, due to increased preferences for biodiversity preservation and increased scarcity due to the continued loss of species from climate change and other causes.

With the baseline assumptions, the estimated SC-CO_2 more than doubles compared to the original FUND 3.9 model, and the sensitivity analysis showed that SC-CO_2 could be more than seven times higher than reported in the original FUND 3.9. As SC-CO_2 estimates are used as decision support and input to Benefit-Cost Analyses of climate change mitigation and adaptation measures (e.g. Greenstone et al. (2013)), our results should be used in the continuous update of these estimates in order to achieve the global economic optimal solution to climate change mitigation and adaptation measures.

Appendix A, tables and figures

A1: Inflation adjustment

Table A1: Weighted average inflation adjustment for each geographical region from 2012 US $ to 2010 US $ and from 2012 US $ to 1995US $, Source: IMF

Region	2012 dollar	2010 dollar	1995 dollar
USA	1.00	0.95	0.67
CAN	1.00	0.95	0.72
WEU	1.00	0.96	0.71
JPK	1.00	0.98	0.73
ANZ	1.00	0.95	0.65
EEU	1.00	0.94	0.20
FSU	1.00	0.92	0.06
MDE	1.00	0.82	0.28
CAM	1.00	0.91	0.34
SAM	1.00	0.91	0.32
SAS	1.00	0.83	0.31
SEA	1.00	0.92	0.33
CHI	1.00	0.94	0.69
NAF	1.00	0.87	0.43
SSA	1.00	0.84	0.16
SIS	1.00	0.88	0.22
World	1.00	0.92	0.46

A2: Total damage in FUND 3.9

Table A2: In FUND 3.9, the total global damage cost is divided into economic damage cost and non-economic damage cost.

Total damage cost in FUND 3.9
• Economic damage cost ▪ Water ▪ Forests ▪ Heating ▪ Cooling ▪ Agricultural ▪ Costs and costal protection ▪ Tropical and extra tropical storms ▪ Income (GDP) ▪ Other economic damage cost • Non-economic damage cost: ▪ Species ▪ Human health: Diarrhea, Vector-borne diseases, Cardiovascular and respiratory mortality ▪ Wetland ▪ Other non-economic damage cost

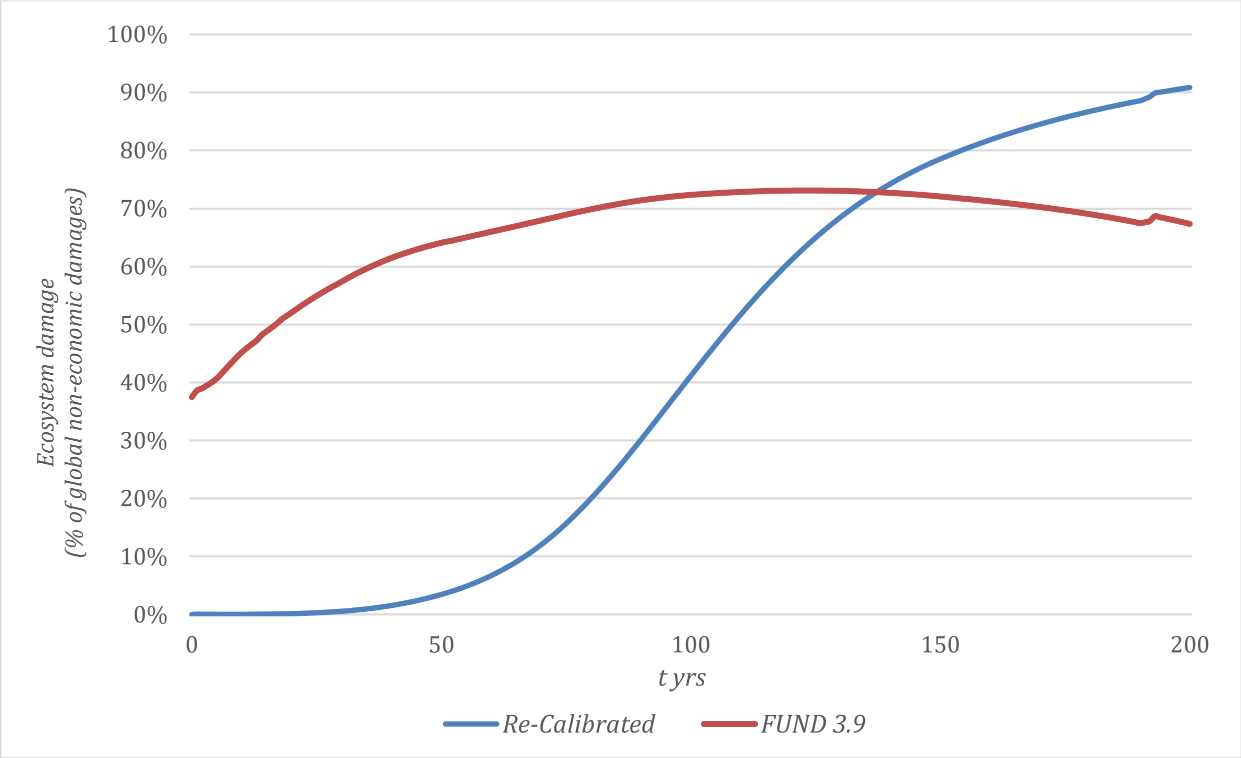

Figure A1: Projection of ecosystem damage cost as a fraction of global non-economic damages cost over time, comparing FUND 3.9 and re-calibrated model. In 1995 US $.

Figure A1 shows the ecosystem damage cost as a fraction of non-economic damage cost, for FUND 3.9 and the re-calibrated model. In FUND 3.9, this fraction starts at a higher share than in our re-calibrated model. Moreover, the share of ecosystem damage costs decreases after approximately 100 years run in FUND 3.9. The re-calibrated ecosystem damage on the other hand starts well below FUND 3.9, but rapidly increases over time. This increment continues beyond the time horizon in figure A1, reaching almost a share of 100%.

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