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Accounting for Biodiversity Loss Raises the Social Cost of CO_2

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Working paper 24-23
December 2024

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Abstract

Scientific evidence of the effects of climate change on biodiversity continues to accumulate. However, economic damages from biodiversity loss go unaddressed in recent updates of the social cost of carbon (SC-CO_2), implicitly assigning biodiversity a zero-dollar value in federal climate policy analyses. Here we show that the value that society places solely on the existence of biodiversity, termed the nonuse value, contributes an additional $8 per tCO_2 to the total. That contribution is on par with the contribution of global energy-use costs and exceeds the contribution of coastal infrastructure loss due to sea-level rise.

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Introduction

The social cost of carbon dioxide (SC-CO_2) represents the global economic damages resulting from an incremental metric tonne of CO_2 emissions (tCO_2) and, conversely, the benefit of mitigating them. Recent advances in estimating the SC-CO_2 account for the effects of climate change on human mortality (Carleton et al. 2022), agriculture (Moore et al. 2017), energy (Rode et al. 2021), and sea-level rise (Diaz 2016). The Greenhouse Gas Impact Value Estimator (GIVE) model (Rennert et al. 2022a)—one of three models underlying the SC-CO_2 estimates now recommended by the US Environmental Protection Agency (US EPA 2023)—finds that those four impact categories alone yield a combined SC-CO_2 of $185 per tCO_2 (in 2020 US dollars, as are all other dollar values stated here), a close match to the standing EPA estimate of $190 per tCO_2. However, GIVE does not yet incorporate many other effects of climate change, including global biodiversity loss. Here we demonstrate that the nonuse value of biodiversity contributes $8 per tCO_2 to the aggregate SC-CO_2, which is on par with the contribution of global costs tied to energy use and greater than the contribution of coastal infrastructure loss caused by rising sea level.

The nonuse value of biodiversity is a subset of the value of biodiversity-related ecosystem services, which are generally described as including all market (Oelmann et al. 2021) and nonmarket (Kolstoe and Cameron 2017) benefits from nature directly or indirectly experienced by people. Examples of ecosystem services separate from nonuse value include hunting and subsistence value, commercial harvest value, and recreational value—anything that involves any form of use. The estimates here pertain only to the nonuse value of species loss and are not meant to represent a fully comprehensive value of species loss. Developing a comprehensive and accurate estimate of the total value of ecosystem services is challenging because of the complex interactions between ecosystems and economies (Druckenmiller 2022). By contrast, nonuse value—that which individuals place on the existence of biodiversity regardless of their own opportunities to experience or utilize its benefits—can be incorporated into the SC-CO_2 by drawing on stated preference methods. This approach is common in many subdomains of economics for cases in which econometric market analyses and revealed preference methods are impractical. Estimating nonuse values is methodologically challenging and subject to critique, but stated preference methods are the most defensible way to elicit them.

Past work made important progress toward incorporating nonuse biodiversity damages into the SC-CO_2, with early estimates suggesting a contribution of approximately $1/$tCO_2$ (Ackerman and Munitz 2012). Brooks and Newbold (2011; hereafter B&N) developed a new approach for estimating willingness to pay (WTP) to prevent species losses from empirical stated preference estimates, calibrating a model to a contingent valuation study (Kramer and Mercer 1997) and a meta-analysis of other stated preference surveys (Richardson and Loomis 2009) focused on the United States (see Methods). Kaushal and Navrud (2023; hereafter K&N) recalibrated the

B&N function to estimate WTP separately for the 16 regions used in FUND (Anthoff and Tol 2014), one of the original SC-CO_2 models. They derive their region-specific parameterizations from a global study using the Delphi method, in which 200 experts from 37 countries responded to a survey about what WTP results they would expect if a contingent valuation study were conducted in their home country (Strand et al. 2017). Here, we incorporate the framework developed by K&N into the GIVE model to estimate the contribution of biodiversity's nonuse value to the SC-CO_2.

Modeling Approach and Results

Developing estimates of the SC-CO_2 entails projecting future climate effects on ecosystems and monetizing the damages of biodiversity losses. Although the role of temperature change in ecosystem dynamics is complex and context dependent (Norby and Luo 2004; Jeppesen et al. 2015; Traill et al. 2010), integrated assessment models commonly employ simplified, reduced-form damage functions that map global temperature rise to intermediate variables and, ultimately, to monetizable metrics. This approach allows for uncertainty in variables throughout the model's economic and physical-climate components and their interactions to be addressed collectively in a statistically robust fashion. To estimate effects of temperature change on species extinction, we re-parameterize the functional form used by B&N and FUND with data from a more recent and comprehensive global meta-analysis (Urban 2015; see Methods). Incorporating this broader data set yields a parameter estimate suggesting that the effect of temperature rise on species loss is 14 percent (−51 to +78 percent: 5–95 percent range) greater than the estimate from B&N and 73 percent (46 to 103 percent: 5–95 percent range) greater than the original fixed value used in FUND.

We integrate those species loss and WTP functions into the GIVE model, which combines stochastic socioeconomic projections of population, economic growth, emissions, and global temperature rise by incorporating empirical and expert-elicitation data into a Monte Carlo simulation. Projections extend to 2300 to capture the vast majority of discounted climate damages (see Methods). GIVE projects a median global surface temperature change of 1.9°C in 2050 (1.5 to 2.4°C: 5–95 percent range) relative to the preindustrial baseline (1850–1900). Corresponding projections for 2100, 2200, and 2300 are 2.5 (1.6–3.9)°C, 3.2 (1.3–6.1)°C, and 3.6 (0.9–7.6)°C, respectively (Fig. 1a).

The temperature trajectories yield uncertain predictions of future species extinctions that cover a wide range of possibilities for economic, policy, and climate system drivers. Our median projection for 2050 is a global species loss of 3.4 percent relative to 2020 (1.3 to 8.7 percent: 5–95 percent range) due to climate change (Fig. 1b). Projected losses grow over time, reaching median values of 5.8 percent (1.6–19.9 percent) in 2100, 7.4 percent (2.1–30.0 percent) in 2200, and 8.2 percent (2.4–34.4 percent) in 2300. These median values are slightly larger than those resulting from

using the parameterization from B&N in GIVE, which are 3.2 percent (1.1–8.7 percent) in 2050, 5.6 percent (1.4–20.0 percent) in 2100, 7.1 percent (1.8–30.1 percent) in 2200, and 7.9 percent (2.1–34.8 percent) in 2300.

After putting the nonuse value of species losses in monetary terms, we estimate the present value of the effect of an incremental ton of CO_2 emissions (Fig. 1c). The partial SC-CO_2 of \$8 per tCO_2 (\$3 to \$16 per tCO_2: 5–95 percent range) associated with the nonuse value of biodiversity is the mean SC-CO_2 value calculated when only biodiversity-related damages are included. For comparison, using the B&N species loss and WTP parameterizations results in a somewhat lower estimate of \$6 per tCO_2 (\$2–\$13 per tCO_2). Most of the increase in the partial SC-CO_2 reflects the updated economic valuation in line with the more recent stated preference methods (Fig. 2).

Including the nonuse value of biodiversity as a damage sector in the broader GIVE model yields a total SC-CO_2 estimate of \$194 per tCO_2 (\$50–\$437 per tCO_2: 5–95 percent range), although this value nonetheless excludes the effects of several important climate-related tipping points (Dietz et al. 2021) and other economic sectors (Prest et al. 2024), which we reserve for future work. By accounting for a well-defined component of the value of biodiversity in the context of a model already used to inform government policy, this improved SC-CO_2 estimate can easily be put into practice.

Methods

We estimate the contribution of the nonuse value of biodiversity to the SC-CO_2 using the GIVE model (Rennert et al. 2022a). GIVE features four modules: (i) long-term probabilistic projections of population, economic growth, and greenhouse gas emissions; (ii) a modern representation of the climate system; (iii) damage functions reflecting both market and nonmarket climate-economy effects; and (iv) a stochastic discounting framework. Detailed descriptions of these methods are available in other articles (Rennert et al. 2022a, 2022b; Newell et al. 2022). Here, we include a brief summary of the socioeconomic projections, the climate model, the species loss function and WTP estimates, and the discounting approach, each of which directly affects the nonuse biodiversity partial SC-CO_2.

Socioeconomics and Temperature Projections

The Resources for the Future Socioeconomic Projections (RFF-SPs) used in GIVE were formulated to address three challenges of calculating the SC-CO_2. First, they take methods widely used to project probabilistic, country-level socioeconomic variables throughout the twenty-first century, and they adapt them to make projections extending to the year 2300 (Rennert et al. 2022b; Raftery and Ševčíková (2023). As with the other damage categories, running the model through 2300 allows us to capture most of the discounted nonuse biodiversity damages in the SC-CO_2 (see Fig.

1c). Second, the RFF-SPs use a combination of econometric, expert elicitation, and Monte Carlo methods to incorporate uncertainty about future economic growth and greenhouse gas emissions. This results in probabilistic projections of emissions that span a wide range of potential outcomes. Lastly, by projecting population and economic growth at the country level, the RFF-SPs allow our damage estimates to reflect important regional differences in how biodiversity is valued (Strand et al. 2017).

Carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) emissions trajectories from the RFF-SPs serve as inputs to a reduced-complexity climate model, FaIR (Smith et al. 2018, version 1.6.2). GIVE accounts for uncertainty in the dynamics of atmospheric and geological systems by using the calibrated 2,237-member parameter set used in the IPCC AR6, which is constrained against both historical observations and behaviors of more complex climate models (Smith et al. 2021).

Species Loss Function

Of the most widely cited integrated assessment models, FUND estimates the largest number of individual categories of economic damages (NASEM 2016), including one specifically addressing ecosystem damages. B&N took the FUND model and replaced its valuation function while retaining a recalibrated version of the species loss function,

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

where B_t is the biodiversity level and ΔT_t is annual temperature change in degrees Celsius, both in year t. The estimated coefficients φ and θ represent the magnitude of the temperature-driven effect and all other drivers of extinction, respectively.

B&N estimate φ using empirical data from three studies (Thomas et al. 2004; Malcolm et al. 2006; Warren et al. 2011), converting temperature and extinction data from those studies' species loss predictions (n = 12) to the annual rates of change used in equation (1), assuming temperature increases linearly and biodiversity declines exponentially. They use those values to calculate implied φ values for each individual trajectory, using θ = 0.001. They then use bootstrapping and model averaging techniques to arrive at their central estimate of φ = 2.62. To account for uncertainty, we reproduce their bootstrapping procedure to generate a random sample (n = 20,000) of values for φ that approximate the nonparametric distribution implied by their model averaging. This approach integrates well with the Monte Carlo sampling inherent in the GIVE model. The mean value of this distribution is φ = 2.64 (1.51 to 3.86: 5–95 percent range), which differs by less than 1 percent from the value they published.

We produce updated estimates of species losses due to climate change using a similar method with an expanded data set of 131 studies covering a variety of model formulations (Urban 2015). We separate their pool of species loss predictions (n =

1,197) by study, prediction year, level of temperature increase, taxon, and region, then calculate per group averages (n = 389) for sample size (species count) and number of predicted extinctions. We then convert these data to constant rates of linear temperature increase and exponential biodiversity decline. We censor three cases where all species in the sample were predicted to go extinct, precluding estimation of exponential biodiversity loss rates. We calculate an implied φ value for each trajectory separately, assuming that predictions in this meta-analysis isolate the effects of climate change, consistent with the author's description of their methodology. We use bootstrapping to randomly sample these φ values, weighted by sample size, resulting in our estimate of φ = 2.77 (2.33 to 3.25: 5–95 percent range). When implementing equation (1) in GIVE, we use the change in average global surface temperature estimated by FaIR as the independent variable and use θ = 0.001 as in B&N.

Biodiversity Damage Function

The B&N model expresses the nonuse value of biodiversity in terms of willingness to pay to avoid a climate-driven biodiversity deficit in year t:

$$wtp_t = y_t - \left[y_t^{1-\eta} + \beta(\eta - 1)\ln(1 + \Delta B_t / B_t)\right]^{1/(1-\eta)}, \quad (2)$$

where B_t and t are the same as in equation (1), ΔB_t is the difference between B_t and a baseline prediction excluding the effect of climate change (i.e., $\Delta B_t = B_{2020}(1-\theta)^{t-2020} - B_t$), y_t is per capita income, and wtp_t is per capita willingness to pay. We quantify biodiversity as the fraction of remaining species relative to the start-year of the model; that is, $B_{2020} = 1$. β and η are estimated parameters that relate the marginal value of biodiversity to net income (i.e., net of WTP):

$$\frac{\partial wtp_t}{\partial B_t} = \frac{-\beta(y_t - wtp_t)^{\eta}}{B_t}. \quad (3)$$

β represents the strength of the preference for biodiversity. η represents the income elasticity of WTP. B&N set $\eta = 2$, citing a rapid-assessment SC-CO_2 model (Newbold et al. 2013), then estimate a single β value using empirical income and willingness-to-pay data from a contingent valuation study (Kramer and Mercer 1997) and a meta-analysis of other surveys (Richardson and Loomis 2009), both of which focus on the United States.

Because GIVE models population and income for 184 individual countries, we draw on more comprehensive and geographically disaggregated estimates of β. We use data from K&N, who estimated β for each of the 16 FUND regions based on a study[16] using the Delphi method (Dalkey and Helmer 1963). K&N set $\eta = 1.5$ for their central case, citing estimates ranging from $\eta = 1$ to $\eta = 2$ taken from studies on the marginal utility of income in general, rather than the income elasticity of nonuse biodiversity value specifically. The source of their WTP estimates (Strand et al. 2017), however, finds an income elasticity of WTP for biodiversity specifically that is close to 1. Hence,

we assume unitary income elasticity ($\eta = 1$). Because we solve for β using equation (2), as did K&N, using a new estimate of η requires recalculating regional β values from their income and WTP data. Although equation (2) is not defined at $\eta = 1$, it has a logarithmic limit that can be derived analytically, yielding this equation:

$$wtp_t = y_t\left(1 - (1 + \Delta B_t / B_t)^{-\beta}\right). \quad (4)$$

Damages are calculated at the country level as the product of national population and per capita willingness to pay (which in turn is a function of country-level GDP per capita), using the β value for the encompassing region:

$$D_{t,c} = P_{t,c}\left[y_{t,c}\left(1 - (1 + \Delta B_t / B_t)^{-\beta_r}\right)\right], \quad (5)$$

where $D_{t,c}$ is nonuse biodiversity damages, $P_{t,c}$ is population, c represents country, and r represents FUND region, with all other variables identical to equations (2) through (4). The application of regional coefficients at the country level is analogous to methods used for some of the other damage sectors in GIVE (Rennert et al. 2022a).

Discounting and SC-CO_2 Estimation

The economic damages associated with biodiversity loss and the other sectors covered by GIVE are converted to present-day values using a Ramsey-like discounting scheme. The Ramsey-like equation takes the form $r_t = \rho + \gamma g_t$, where r_t is the discount rate over time, ρ is the pure rate of time preference, γ reflects the elasticity of the marginal utility of consumption, and g_t is the rate of per capita consumption growth from the year of the emissions pulse to year t. We use $\rho \approx 0.2\%$ and $\gamma \approx 1.24$, values empirically calibrated to be consistent with the RFF-SPs (Rennert et al. 2022b) and with observed behavior of interest rates (Bauer and Rudebusch 2020). This corresponds to a near-term risk-free rate of approximately 2 percent.

We estimate the nonuse biodiversity partial SC-CO_2 by running the model twice, once as a baseline and then again after adding a "pulse" of 0.1 Mt to the CO_2 emissions in the first year. We chose 2020 as the year for the emissions pulse to match the baseline GIVE model. Damages calculated in equation (5) are aggregated from the country level to the global level ($D_t = \sum_c D_{t,c}$) for each of the two runs, and then marginal damages are calculated by subtraction: $\mathrm{MD}_t = D_t^{\text{pulse}} - D_t^{\text{baseline}}$. These are discounted by the stochastic discount factor (SDF_t), an equivalent expression of the discounting scheme described above:

$$\mathrm{SDF}_t = \frac{1}{(1+\rho)^{t-2020}}\left(\frac{\mathrm{CPC}_t}{\mathrm{CPC}_{2020}}\right)^{-\gamma}, \quad (6)$$

where CPC_t represents global consumption per capita in year t, which is based on projected global GDP minus baseline damages from the five sectors covered by GIVE, including biodiversity damages. The SC-CO_2 is calculated as the sum of the discounted marginal damages ($\sum_{t=2020}^{2300} \mathrm{SDF}_t \times \mathrm{MD}_t$) divided by the pulse size to

reach a final value corresponding to a single metric ton of CO_2. This is computed for each individual Monte Carlo draw.

We estimate the SC-CO_2 for three parameterizations of our model corresponding to (i) the original B&N methods for modeling both species loss and its valuation; (ii) using only our updated estimate of the species loss coefficient φ; and (iii) our preferred method, using both the new φ and the updated regional β values. We run a Monte Carlo simulation for each case (n = 10,000) and present mean values as our central estimates, corresponding to economic theory for valuing uncertain costs (Rennert et al. 2022a; Gollier 2001).

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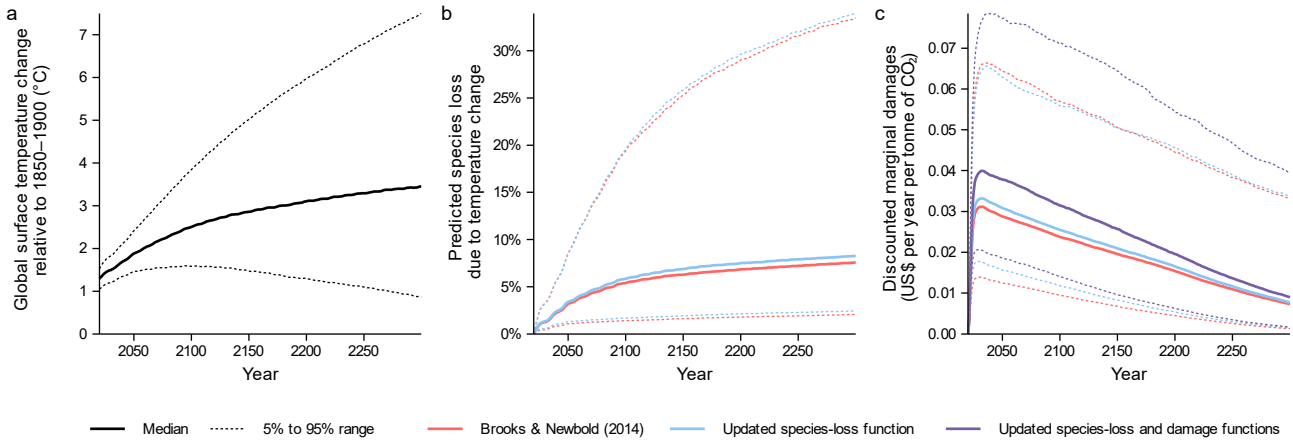
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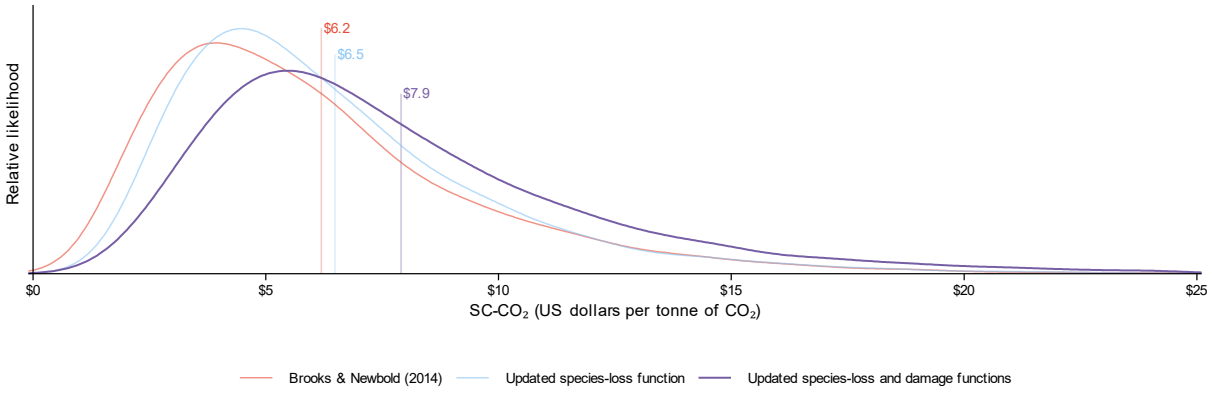
Figures

Figure 1. Projected Temperature Change, Species Loss, and Discounted Marginal Damages



a, Predicted global surface temperature change in °C, relative to 1850–1900 preindustrial baseline. **b**, Predicted species loss due to temperature change for different model configurations, expressed as percentage of total species-level biodiversity. **c**, Nonuse value of predicted biodiversity losses for a marginal pulse of one ton of CO_2 emissions in 2020, disaggregated by year and discounted to present-day value. "Brooks & Newbold" lines indicate that B&N parameters were applied in GIVE model. In all graphs, solid lines represent median values and dashed lines represent boundaries of 5–95 percent range.

Figure 2. Uncertainty Distribution of Partial SC-CO_2 for Nonuse Biodiversity Value



Vertical lines and annotations show mean value corresponding to each parameterization of model. "Brooks & Newbold" lines indicate that B&N parameters were applied in GIVE model.

