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Climate Impacts on Terrestrial Ecosystems: Consequences for Human Well-being and Economic Growth

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Climate Impacts on Terrestrial Ecosystems:
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Abstract

Humans derive benefits from ecosystems in multiple ways. As ecosystems move and are disrupted by the changing climate, these benefits will change or disappear. In this dissertation, I explore what are the consequences to society of those changes on market and non-market components of human well-being provided by ecosystems throughout the globe. I use an integrated approach to model the interactions between climate, economics and ecosystems, allowing to estimate climate policy-relevant metrics such as the social cost of carbon.

The Introduction of this dissertation is a review of the state of the literature on natural capital and the social cost of carbon highlighting key research areas to advance this field. The first chapter presents GreenDICE, an Integrated Assessment Model (IAM) that extends the standard Dynamic Integrated Climate-Economy (DICE) model to account for natural capital and its role in providing use and non-use benefits to people. The second chapter extends GreenDICE to account for process-based ecosystem dynamics and allow for geographical heterogeneity among countries in relation to their dependence on natural capital for the creation of market and out-of-market goods and services. Finally, the third chapter turns to the empirical question of whether there is evidence of persistent effects of temperature on gross domestic product (GDP), such as the ones we would expect to see in an economy that relies on productive assets that in turn are damaged by climate change, as in the case of natural capital in GreenDICE.

Overall, the results show that explicitly including ecosystems as a form of capital assets in IAMs increases by an order of magnitude the social cost of carbon. Moreover, these impacts will not be equally distributed across the world. The market economies of low-income countries will be

the most affected by climate change-disturbed ecosystems, posing an additional mechanism for intensifying inequality. The empirical evidence shows that it is likely that some country-level economies might have already experienced persistent temperature effects on GDP, supporting modeling approaches as GreenDICE that include temperature impacts on the economic productive base.

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Climate Impacts on Natural Capital: Consequences for the Social Cost of Carbon

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Abstract

The effects of climate change on natural systems will be substantial, widespread, and likely irreversible. Warmer temperatures and changing precipitation patterns have already contributed to forest dieback and pushed some species toward extinction. Natural systems contribute to human welfare both as an input to the production of consumption goods and through the provision of nonuse values (i.e., existence and bequest values). But because they are often unpriced, it can be difficult to constrain these benefits. Understanding how climate change effects on the natural capital stock affect human well-being, and therefore the social cost of carbon (SCC), requires understanding not just the biophysical effects of climate change but also the particular role they play in supporting human welfare. This article reviews a range of topics from natural capital accounting through climate change economics important for quantifying the ecological costs of climate change and integrating these costs into SCC calculations.

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INTRODUCTION

Anthropogenic climate change will alter patterns of temperature, precipitation, and weather extremes around the world throughout the twenty-first century and beyond. Even with ambitious mitigation policies in place, rates of warming will exceed anything in the historical record and likely anything in the last tens or even hundreds of thousands of years of Earth history (Tierney et al. 2020). Although rapid progress has been made in recent years in understanding the sensitivity of socioeconomic outcomes to weather fluctuations and climate change (Carleton & Hsiang 2016, Dell et al. 2014, Piontek et al. 2021), some of the most direct, pervasive, and irreversible effects of climate change will occur on ecological systems. Climate change will alter the productivity of natural systems, shift patterns of terrestrial vegetation, and push a potentially large number of species to extinction (Scholes et al. 2014, Urban 2015). Changes in the flows of valuable goods and services derived from these systems have implications for human welfare, but they are only imperfectly captured in current estimates of the aggregate costs of greenhouse gas emissions, such as the social cost of carbon (SCC).

This article both reviews work on natural capital's role in the economy and human welfare and walks through how incorporating this theory into standard models of the coupled climate-economic system might alter estimates of climate change costs, with implications for policy-relevant quantities like the SCC. The focus of this review is on the welfare effects of the ecological impacts of climate change impacts, excluding a more general discussion of the many interactions between climate change and natural systems. For instance, deforestation results in threats to biodiversity and the loss of ecosystem services and also contributes to climate change through the release of carbon dioxide (CO_2) into the atmosphere. In addition, natural systems face anthropogenic threats other than climate change, such as habitat destruction or local air and water pollution, which in many cases will be the most important determinants of ecosystem quality over the twenty-first century. Climate change will interact with these other environmental threats in complex ways, but those interaction effects are not discussed here. We also focus on ecosystem services other than agricultural production. Although agriculture is both heavily exposed to climate change impacts and dependent on natural capital inputs such as soil fertility, there is a large literature dedicated to the effects of climate change on agriculture, the review of which is necessarily outside the scope of this article (for recent reviews of this topic, see Antle & Stöckle 2017, Blanc & Schlenker 2017, Carter et al. 2018).

We begin with a brief review of the concept of the SCC, how it is calculated, and how ecological impacts are (or are not) integrated into models currently used to estimate it. We then provide background on the definition and measurement of natural capital and describe the expected biophysical effects of climate change before reviewing how these effects can be integrated into standard climate-economy models.

THE SOCIAL COST OF CARBON AND THE REPRESENTATION OF ECOLOGICAL DAMAGES

The SCC in year t is defined as the net present value of the impacts of one ton of CO_2 emitted into the atmosphere in that year. The SCC is specific to the baseline emissions path; in economic research it is often calculated along an optimal emissions pathway, where the global carbon tax is set equal to the SCC (Nordhaus 1992). In policy applications, however, the SCC is typically calculated along a nonoptimal no-policy-emissions trajectory (Rose et al. 2017). Calculating the SCC requires connecting greenhouse gas emissions to human welfare, which requires modeling the carbon cycle (emissions to atmospheric CO_2 concentration), the climate system (CO_2 concentration to global temperature), and the damages from climate change (temperature to human

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welfare). These calculations are done using cost-benefit integrated assessment models (IAMs), of which the three most widely used today are the DICE, PAGE, and FUND models (Anthoff & Tol 2014, Hope 2011, Nordhaus 2017).

Climate damages included in the SCC are, in principle, fully comprehensive. Even though everything is denominated in monetary units (e.g., US dollars), damages should include nonmarket impacts such as mortality and morbidity, effects on natural systems, and loss of cultural heritage. Exactly how climate change impacts on natural capital are incorporated into these models is not always obvious. They are explicitly modeled only in FUND, which includes both damages associated with wetland loss to sea-level rise based on a meta-analysis of ecosystem services provided by wetlands by Brander et al. (2006) and a damage function capturing the nonuse values of biodiversity decline, with values based on the study by Pearce (1993). Calibrations of these functions result in empirically small effects, contributing vanishingly small amounts to FUND's SCC (Diaz & Moore 2017, Rose et al. 2017).

Ecological impacts in PAGE are in theory captured in the nonmarket damage function, along with mortality damages, although the exact empirical basis for calibration of this damage function, and therefore the degree to which it does or does not include natural capital costs, is difficult to determine. DICE aggregates all impacts into a single damage function based on a weighted meta-analysis of studies reporting global welfare changes at different levels of warming (Nordhaus & Moffat 2017). However, as pointed out by Howard & Sterner (2017), a substantial fraction of these studies use regressions of gross domestic product (GDP) on temperature or temperature change and are therefore missing nonmarket and nonuse impacts derived from ecosystems. Sector-based studies using computable general equilibrium models capture some sectors dependent on natural capital such as agriculture and forestry (Johnson et al. 2021), but it is fair to say that ecological climate damages are not explicitly, and in most cases not implicitly, represented in the studies supporting the DICE damage function.

One important exception to note is the case of carbon sequestration. Often included as an important component of the ecosystem services provided by landscapes, carbon sequestration plays a particular role in SCC calculations. Because any SCC calculation requires translating CO_2 emissions into temperature change, it requires some implicit (via parameterization) or explicit representation of uptake of carbon from the atmosphere by the biosphere (i.e., carbon sequestration), usually as part of a simple carbon-cycle model within the IAM. Currently the biosphere takes up about 30% of anthropogenic emissions to the atmosphere (Friedlingstein et al. 2020), but it is likely this sink will weaken with future climate change as warming and drought disrupts terrestrial vegetation growth (Anderegg et al. 2020, Hubau et al. 2020). Dietz et al. (2021) point out that carbon cycle models within the IAMs used to calculate the SCC are missing this weakening biospheric sink as well as a similar feedback that reduces the size of the ocean sink as a function of warming. They estimate that omission of these carbon cycle feedbacks leads to an underestimate of the SCC by about 10% in 2020, growing to over 20% by 2100. Because carbon sequestration is explicitly represented within IAMs as part of the SCC calculations, discussion in the rest of this review should be understood as the effects on ecosystem services other than carbon storage.

NATURAL CAPITAL AND ECOSYSTEM SERVICES

This section presents a review of the concept, definition, and measurement of natural capital and ecosystem services before discussing how these can be incorporated into IAMs and therefore better represented in SCC calculations.

Broadly speaking, the motivation for natural capital accounting and ecosystem service valuation arises from the observation that natural systems provide a range of benefits to humans. Because

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many ecological goods are common-pool resources or public goods, many are characterized by imperfect property rights and therefore their full value will not be reflected in market transactions or national accounting data such as GDP. The set of benefits derived from natural systems can be divided into use and nonuse goods (Turner et al. 2003). Use values of nature arise when natural systems interact directly with the society or manufactured capital, such as the flood-protection benefit mangroves provide to coastal cities or the raw materials used in producing market goods. Nonuse values arise without interacting with nature, which could be either for the sake of nature itself (existence value) or the sake of future generations [bequest value (Krutilla 1967)].

Natural capital is part of society's productive base, producing flows of ecosystem services. The analogy is to more typical forms of capital assets, which are stocks of wealth that can be used to produce a flow of benefits into the future. Following Dasgupta (2014), the total natural capital stock at time t can be written as the sum over individual natural assets (e.g., soils, forests, wetlands) multiplied by their shadow price:

$$N(t) = \sum_i p_i(t)\, n_i(t). \qquad 1.$$

The shadow price $p_i(t)$ gives the present value of the stream of benefits derived from an additional unit of the natural asset, conditional on the socioeconomic policies in place and the natural capital growth deriving from ecological dynamics and human impact.

Building on capital pricing theory, Fenichel & Abbott (2014) further develop the determinants of the asset price $p_i(t)$. They derive an expression that describes this price as a function of the marginal change in the flow of ecosystem services with an increase in the natural capital stock (which in turn will depend on the specifics of institutions managing access to the ecosystem goods), modified by a capital gains term associated with changing scarcity value and divided by the discount rate adjusted for the changing growth dynamics from marginally higher stocks.

Applications of this approach have included valuing fisheries stocks, including under nonoptimal management (Fenichel & Abbott 2014), and the agricultural value of the Kansas High Plains Aquifer (Fenichel et al. 2016a). For ecosystem goods other than crops, fish, or timber (where market prices are readily observable), measuring the marginal dividends (change in the flow of benefits with a marginal change in the capital stock) can be particularly challenging because it requires the application of nonmarket valuation approaches. Accounting for nonuse values such as existence and bequest values adds further complexity, as these can be measured only using stated-preference approaches. Some studies have argued that these values can be bounded from below using observations of the costs societies are willing to undertake to preserve species existence, although these tend to be two orders of magnitude lower than stated preference estimates (Maher et al. 2020, Moore et al. 2022).

MEASURING GLOBAL NATURAL CAPITAL STOCKS AND SUSTAINABILITY

A challenge with integrating natural capital accounting into SCC estimates is that, because climate change is a global externality, anything less than full global coverage is insufficient for SCC calculations. Both the World Bank and the United Nations Environment Programme (UNEP; Managi & Kumar 2018, World Bank 2006, 2011) have been developing approaches to incorporate natural capital accounting into national accounts data. The World Bank *Wealth of Nations* report (Lange et al. 2018) includes energy and mineral deposits, cropland, and timber and nontimber services from forests and protected areas. Valuation of energy, minerals, timber, and agricultural land uses market prices, whereas nontimber forest benefits are based on a meta-analysis of forest ecosystem services by Siikamäki et al. (2015). Protected areas are valued only using the option value of pasture or cropland that might be grown on the land, making it a lower-bound estimate missing any recreational or nonuse values derived from those areas. The UNEP *Inclusive Wealth Report* (Managi & Kumar 2018) undertakes a similar exercise, but it also includes valuation of fisheries stocks and a broader array of nontimber forest benefits based on the Ecosystem Service Valuation Database by van der Ploeg & De Groot (2010).

Including measures of natural capital assets in national accounts is critical for operationalizing the concept of sustainability, which is typically defined as ensuring non-declining intergenerational well-being (Arrow et al. 2012). Because well-being derives from a (broadly defined) set of assets, this sustainability criterion is equivalent to ensuring that the value of these assets is not declining over time (Dasgupta 2021, Dasgupta & Mäler 2000, Hamilton & Clemens 1999). In other words, a fully comprehensive or inclusive measure of wealth including natural capital, human, institutional, and social capital, as well as more traditional manufactured capital, should be steady or increasing (Dasgupta 2001, Hamilton & Hartwick 2014). This definition of sustainability allows for substitution between natural and other forms of capital and for that reason is sometimes called weak sustainability (Pearce & Atkinson 1993). However, even using this weak form of sustainability, UNEP's 2018 *Inclusive Wealth Report* found that only 84 out of 140 countries met this criterion (Managi & Kumar 2018).

ECOLOGICAL IMPACTS OF CLIMATE CHANGE

Anthropogenic emissions of greenhouse gases affect natural systems through a number of pathways, including CO_2 fertilization, ocean acidification, sea-level rise, and changes in temperature and rainfall patterns. **Figure 1** illustrates some of the most important pathways by which these climate drivers map, via ecological changes, into changes in ecosystem service provisions, with implications for human welfare.

Higher CO_2 concentrations in the atmosphere are partially taken up both through the biosphere via higher primary productivity [i.e., the CO_2 fertilization effect that has taken up approximately 30% of anthropogenic emissions in the 2010–2019 decade (Friedlingstein et al. 2020)] and abiotically via dissolution in the ocean as carbonic acid [22% of 2010–2019 emissions (Friedlingstein et al. 2020)], contributing to ocean acidification. The remaining airborne fraction of anthropogenic CO_2 emissions disrupts the radiative balance of the planet and contributes to climate change, the most immediate and most widespread consequence of which is higher temperatures.

Higher temperatures, particularly rates of warming projected for the twenty-first century [likely unprecedented in the tens of millions of years of Earth history (Tierney et al. 2020)], can disrupt ecological systems in a number of ways. In arid areas, higher temperatures will increase the severity of droughts, even absent any changes in rainfall: Agricultural and ecological measures of drought severity are based on the balance between the supply of water to a region (via precipitation) and the atmosphere's demand for that water via evapotranspiration (Dai 2013, Touma et al. 2015). Because evapotranspiration increases rapidly at higher temperatures, hotter droughts dry out soil moisture more rapidly and can have more severe agro-ecological effects than cooler droughts (AghaKouchak et al. 2020, Diffenbaugh et al. 2015, Zscheischler et al. 2020).

Large-scale diebacks of forests worldwide have been linked to climate change, via both drought and the spread of pests and diseases better able to survive winters in the warmer climate (Seidl et al. 2017). A concern is that widespread tree mortality will partly offset, or even eliminate, the biospheric carbon sink, leading to more rapid CO_2 accumulation in the atmosphere and even faster climate change (Anderegg et al. 2020, Hubau et al. 2020). Changes in temperature, rainfall, and CO_2 concentrations will redistribute terrestrial vegetation globally. Most models project

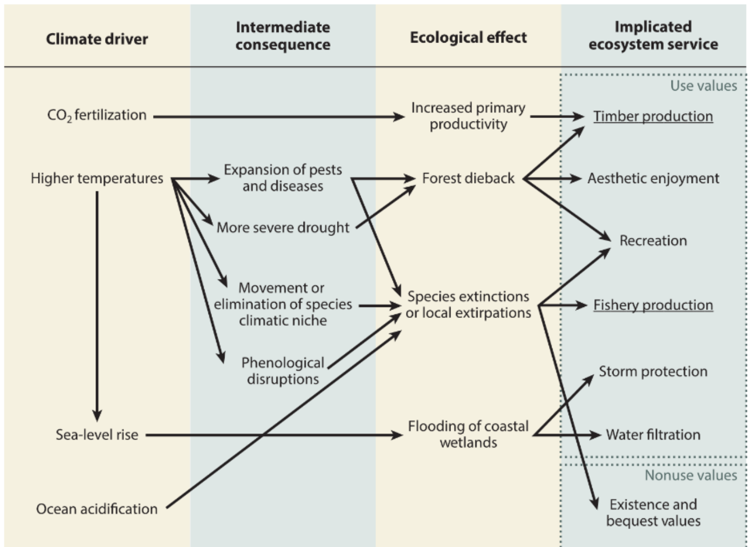

Figure 1

Diagram relating some of the most well-understood, direct, and widespread physical effects of greenhouse gas emissions (*left*, climate driver) to their ecological effects on natural or lightly managed systems and on human welfare via ecosystem service provision. This is not an exhaustive catalog of the effects of climate change on natural systems, and there may be additional important impacts in particular locations. Ecosystem services are categorized into use and nonuse values. Underlining indicates market goods.

reductions in vegetative carbon over the Amazon region and increases in boreal ecosystems (Sitch et al. 2008).

Climate is a key predictor of species distributions: Ecologists describe species as having a particular climate niche or a range of preferred temperature and rainfall in which the species is observed (Wiens et al. 2009). Rising temperatures will change the locations of that climate niche, in most cases pushing it toward higher latitudes or up in altitude. If a species' climate niche ceases to exist, or if the rate of dispersal (movement across space) is unable to track the speed of climate change, then the species may be at risk of extinction. Many studies in ecology have used species range maps combined with climate model projections to estimate the fraction of species threatened with extinction by climate change. For example, Urban (2015) reviewed 131 such studies, finding that on average these studies project −5.2% of species to be at risk of extinction under 2° of warming and 8.5% under 3°.

These estimates based mostly on climate niche modeling are likely to underestimate, perhaps substantially, the full effect of climate change on extinction risk, as they largely do not account for interactions between species. For instance, warmer temperatures can change the seasonal timing (phenology) of plant reproduction, a particular problem for migratory species relying on specific plants or habitats at particular times (Robinson et al. 2009). Coral reefs are threatened by both ocean acidification and warmer temperatures driving increasingly frequent marine heatwaves

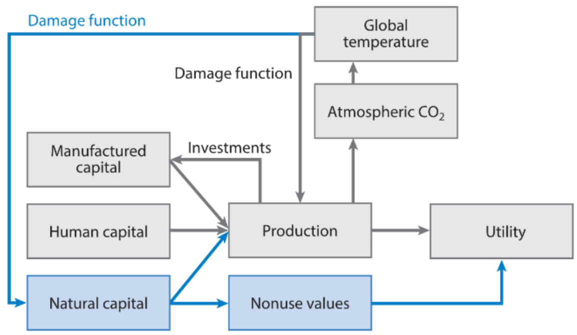

Figure 2

Schematic diagram of the canonical DICE integrated assessment model (*gray*) with expansions proposed by Bastien-Olvera & Moore (2021) (*blue*) to explicitly model the role natural capital plays in contributing to human welfare and the impacts of climate change on ecological systems.

(Hughes 2003) and provide habitat for large fractions of marine species, many of which will be affected if coral reefs disappear (Jones et al. 2004). Expanding ranges of pests and diseases can threaten refugia of endangered species, as recently documented for white bark pine in the Sierra Nevada (Dudney et al. 2021).

INCORPORATING NATURAL CAPITAL INTO THE SOCIAL COST OF CARBON

Gray boxes and arrows in **Figure 2** schematically represent the canonical DICE IAM developed by William Nordhaus (1992, 2017). In this representative agent model, labor (or human capital) and manufactured capital produce economic output using a Cobb–Douglas production function. Production is split between savings, which is invested in the depreciating capital stock, and consumption, which contributes to utility. Production is also associated with greenhouse gas emissions that increase the stock of CO_2 in the atmosphere, which in turn increases global temperature. This has a negative effect on production via the damage function. CO_2 emissions from production can be reduced, at some cost, via mitigation (not shown). The savings and mitigation rates each time period are optimized to maximize discounted utility.

Figure 2 also shows an expansion of the DICE framework, following Bastien-Olvera & Moore (2021), to explicitly model the role of natural capital in production and utility as well as the ecological impacts of climate change represented as a second damage function. This expanded framework explicitly represents the role of natural capital in producing both use values, as an input to production, and nonuse values, as a direct input into the utility function. Subsequent sections of this review walk through the three primary modifications of DICE in this framework—the production function, the utility function, and the damage function—and discuss how explicitly representing natural capital damages might affect estimates of climate change costs.

Production Function

Economic output in DICE is given by the classic Solow–Swan growth model (Solow 1956) in which exogenously growing total factor productivity, exogenously growing population, and an endogenous capital stock determine production and growth.[1] Labor and capital (generally understood to mean manufactured capital) are the two factors of production, moving away from earlier work that had considered land as a third factor (Gaffney 2008). In his original work, Solow explicitly states that "there is no scarce nonaugmentable resource like land" (Solow 1956, p. 67), effectively assuming that land, resources, or natural systems more generally impose no fundamental constraint on production.

The question of whether natural resources belonged in the production function as a third factor of production was an active area of research and debate in the 1970s, partly prompted by work such as *The Limits to Growth* (Meadows et al. 1972) that predicted economic collapse upon exhaustion of resources. Criticism of this work by economists emphasized the importance of establishing the substitutability between natural resources and other inputs in production (e.g., Stiglitz 1974). If these natural resources (N) are perfectly substitutable with capital and labor [i.e., $Y = A(\alpha_1 K + \alpha_2 L + \alpha_3 N)$, where A is total factor productivity], then they impose no fundamental limit on production and "the world can, in effect, get along without natural resources, so exhaustion is just an event, not a catastrophe" (Solow 1974, p. 11). If instead resources are only partially substitutable with other inputs, for instance, in a three-factor Cobb–Douglas production function [i.e., $Y = A(K^{\alpha_1} L^{\alpha_2} N^{\alpha_3})$, a special case of a constant elasticity of substitution production function],[2] then production can be maintained for any nonzero value of N but requires increasing inputs of labor and capital as N declines.

Bastien-Olvera & Moore (2021) substitute DICE's two-factor production function for a three-factor Cobb–Douglas production function with constant returns to scale:

$$Y = A(K^{\alpha_1} L^{\alpha_2} N^{\alpha_3}), \text{ where } a_1 + a_2 + a_3 = 1. \qquad 2.$$

Assuming the natural capital stock N is fixed, then this change alone slows baseline economic growth rates, even with an optimized savings rate, since a growing population and capital stock translate into smaller increases in production. If the stock of natural capital is declining, for instance due to the impacts of climate change, then those impacts will affect the growth rate and have a long-lived effect on the level of output, similar to other persistent climate change damages such as effects on the depreciation rate or on total factor productivity growth (Kikstra et al. 2021, Moore & Diaz 2015).

In reality, the natural capital stock N is unlikely to remain fixed even in the absence of climate change. Renewable resources such as fisheries or forests exhibit biophysical growth dynamics related to the carrying capacity of the system and the natural rate of increase (Anderson & Seijo 2010). Externalities of human activity other than climate change might also affect the dynamics of the stock (Hackett & Moxnes 2015, Liang et al. 2021). Finally, society might also divert part of production into investments to restore, replenish, or expand the natural capital stock, just as production is invested in manufactured capital in the standard DICE model. Bastien-Olvera & Moore (2021) model this possibility and find that relaxing the constraint on the size of the natural capital stock by allowing investment of output in a natural capital asset leads to large investments

[1]Note that the other major IAMs calculating the SCC (FUND and PAGE) do not include a growth model. Instead, population and per-capita GDP growth are specified exogenously.

[2]The Cobb–Douglas production function imposes a constant elasticity of substitution equal to one. However, the closer to zero the elasticity of substitution gets, the less the substitutability between the factors of production. The choice of this parameter and the assumption that it is constant have been widely used in economics due to its mathematical tractability, but this is a particular modeling choice that could be more widely investigated.

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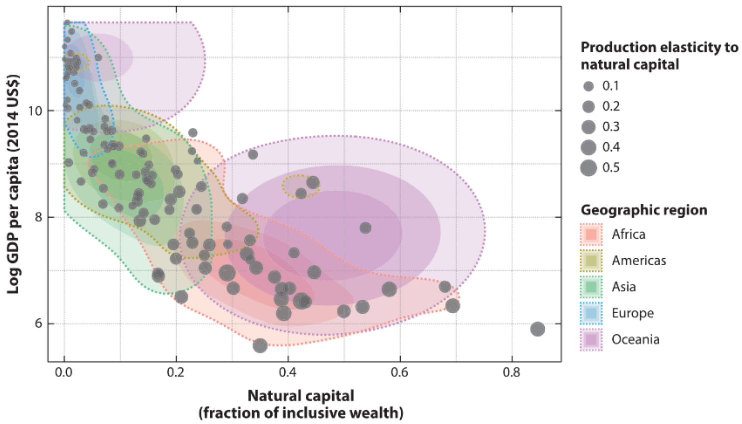

Figure 3

The relationship between gross domestic product (GDP) per capita and the fraction of total inclusive wealth made up by natural capital, excluding minerals and oil. Color shadings indicate the areas with higher densities of data points for each geographic region. Figure based on data from the World Bank Open Data (**https://data.worldbank.org/**).

and much larger stocks. However, it is still unclear how effective these hypothetical investments could be in growing the natural capital stock.

The DICE model has just one global region, but reliance on natural capital for economic production is not uniform around the world. In particular, global accounting of natural capital by the World Bank and UNEP (discussed above) documents a particular reliance on natural capital in poorer economies: As countries get richer, their stocks of manufactured and human capital grow, and the relative importance of natural capital in national assets declines (**Figure 3**).

Variation across countries in the importance of domestic natural capital in production implies there will be heterogeneity in the welfare effects of climate change's ecological impacts, even if the biophysical effects were identical across countries. Because economic production in low- and lower-middle-income countries relies heavily on provisioning and regulating ecosystem services such as pollination, forests, and fisheries (Johnson et al. 2021), these effects are likely to be regressive: The same fractional reduction in the natural capital stock will lead to larger output declines in poorer countries than in richer countries. In reality, there are reasons to believe that biophysical effects of climate change might also be worse in poor countries, which also tend to be warmer. For instance, while high northern latitudes might see expansion of forests, forest dieback is projected in at least some tropical regions (Sitch et al. 2008). Similarly, cooler richer countries might see migration of fish stocks into territorial waters, whereas poorer, warmer countries might see net outflows (Cheung et al. 2009). The distributional effects of climate impacts become more pronounced when considering impacts in nonpriced goods that comprise the largest welfare source in societies with subsistence economies (Hertel & Rosch 2010). This pattern also appears to hold for within-country income groups. For instance, Hsiang et al. (2017) show that county-level climate damages in the United States increase by approximately one percent for each reduction in income decile.

These distributional effects are lost if using only a single-region global model and require the use of more highly resolved, multiregion models. Regressive climate change impacts can substantially increase the SCC if using equity weighting, which takes into account different marginal utility of consumption to aggregate across regions (Anthoff & Emmerling 2019, Dennig et al. 2015).

Utility Function

The production function discussed above describes the dependence of economic production on natural capital. But nonuse values of nature, such as existence and bequest values, have long been recognized (Krutilla 1967). Through the production of nonuse values, natural capital might also enter directly into utility, providing benefits to people independent of any role in economic production. This section discusses the representation of utility in SCC calculations and particularly how nonmarket or nonuse values enter into utility and determine the welfare consequences of climate change–driven impacts to natural capital.

The utility function plays a critical role in determining the welfare costs of climate change. Climate change impacts are long lived, uncertain, and unequally distributed, and there is a substantial literature documenting how parameters of the utility function such as the discount rate, risk aversion, and inequality aversion affect the SCC (Anthoff & Emmerling 2019, Anthoff et al. 2009, Nordhaus 2007). A much smaller literature, however, has also documented how assumptions regarding the substitutability of goods in the utility function can also have important implications for the welfare effects of climate change.

First described as intangibles (Tol 1994) and subsequently as environmental goods (Hoel & Sterner 2007) or nonmarket goods (Drupp & Hänsel 2020), the insight from these papers is that some unknown, but potentially large, fraction of climate change damages will fall on nonmarket goods such as health and mortality, recreation and leisure, or ecosystem goods and services. Assumptions about how impacts to these goods interact with more typical market consumption goods in the utility function can be an important, but often overlooked, driver of results from IAMs.

Although all cost-benefit IAMs that calculate the SCC in principle include a full suite of damages encompassing both market and nonmarket goods, these are modeled as falling on a single consumption good. In DICE, for example, utility of the representative agent is given by constant relative risk aversion utility:

$$u(c_t) = \frac{c_t^{\eta}}{1-\eta}, \qquad 3.$$

where η is the coefficient of relative risk aversion that parameterizes the curvature of the utility function. Climate change damages through both market and nonmarket channels are modeled as falling on the aggregate consumption good c. As Sterner & Persson (2008, p. 68) describe, this assumes perfect substitutability between climate damages and consumption of market goods: "one dollar's worth of climate damages, regardless of the kind, can be compensated by a dollar's worth of material consumption."

Alternate utility functions relax this assumption to allow market and nonmarket goods to enter the utility function separately. For instance, Tol (1994), Weitzman (2012), and Brooks & Newbold (2014) propose additively separable utility function, in which some damages accrue on a second environmental good, shown here as e_t:

$$u(c_t, e_t) = f(c_t) + g(e_t). \qquad 4.$$

Brooks & Newbold (2014) consider in particular the nonuse values of biodiversity and argue that this utility value is largely independent of values derived from consumption of market goods and services, in contrast to other use values provided by ecosystems. Weitzman (2012, p. 60) similarly argues that utility derived from "things that are not readily substitutable with material wealth, such as biodiversity and health" might be captured in this additive term.

Other authors considering two-good utility functions in the context of climate damages, beginning with Hoel & Sterner (2007) and Sterner & Persson (2008), have used constant elasticity of substitution (CES) utility functions given by

$$u\left(c_t, e_t\right) = \frac{1}{1-\eta}\left(\alpha c_t^{\theta} + (1-\alpha)\, e_t^{\theta}\right)^{\frac{1-\eta}{\theta}}, \qquad 5.$$

where, as in Equation 3, η parameterizes the curvature of the utility function, θ gives the degree of substitutability between consumption and environmental goods, and α gives the shares of utility arising from the two goods.

Equation 5 includes a number of difficult-to-estimate parameters. Values used in the literature for θ have ranged widely, from partial complements [$\theta = -1$ in Hoel & Sterner (2007) and Sterner & Persson (2008); $\theta = -0.33$ in Kopp et al. (2012)], to partial substitutes [$\theta = 0.6$ in Bastien-Olvera & Moore (2021)]. This value is theoretically related to the income elasticity of willingness to pay for environmental goods (Baumgärtner et al. 2015, Ebert 2003). Reviews of estimates of these income elasticities reported in the literature suggest that environmental goods are weak to moderate substitutes for consumption goods, with θ values roughly between 0.2 and 0.6 (Baumgärtner et al. 2015, Drupp 2018, Drupp & Hänsel 2020).

Figure 4 schematically illustrates how different values of θ determine both utility growth over time and climate change impacts. The underlying model includes constant growth in the consumption good c_t but no growth in the environmental good e_t. Even absent climate change damages (**Figure 4*a***), the differential growth rates of the two goods interact with θ to produce different utility pathways over time: Under complementarity (i.e., $\theta < 0$), the fixed flow of e_t constrains the utility derived from the growing consumption good c_t, resulting in slower utility growth than if the two goods are substitutes (i.e., $\theta > 0$).

Figure 4*a* also shows utility growth if the environmental good gradually declines over time due to climate change damages. Once again, depending on θ, the same changes to the environmental good produce much larger changes to utility (both proportionally and in absolute terms) under complementarity than under substitutability. **Figure 4*b*** illustrates the present value of these damages under a 2% utility discount rate and shows the same biophysical climate impacts (i.e., the same reductions in the flow of the environmental good) produce welfare costs 7 times higher under $\theta = -1$ compared to $\theta = 1$.

The CES function, as its name would suggest, uses a constant value of θ over the range of environmental goods, which could be a good approximation for small changes in the relative scarcity of different types of goods. However, the elasticity of substitution might well fall as the environmental good becomes very scarce, implying much larger marginal climate change damages at low levels of the natural capital stock. This case would also imply an important interaction effect between climate damages and other drivers of ecosystem decline: If other anthropogenic impacts over the twenty-first century such as habitat loss or air and water pollution cause a substantial diminishment of the natural capital stock with a corresponding decrease in substitutability, then additional losses from climate change will be more damaging than in the absence of those other drivers.

Damage Function

The section titled Ecological Impacts of Climate Change discussed evidence from the ecological literature on how climate change is likely to alter ecosystem productivity and raise extinction risk for many species. These damages all ultimately have implications for the contributions of

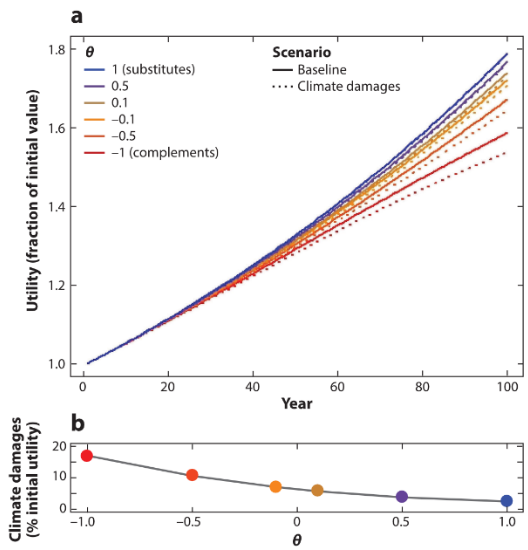

Figure 4

(*a*) Baseline utility growth (*solid lines*) with a growing consumption good and fixed environmental good and constant elasticity of substitution utility under different substitutability parameters (θ). Dotted lines show utility growth if the environmental good gradually declines over time due to climate damages. (*b*) Present value of climate damages shown in panel *a* (difference between *dotted lines* and *solid lines*) under a 2% utility discount rate as a function of θ.

natural systems to human welfare, as shown in **Figure 1**. These services range from market goods such as timber and fish production, nonmarket goods such as storm protection or recreational opportunities, and nonuse values such as existence and bequest values.

Capturing these changes in SCC calculations requires valuing their effects in order to parameterize a damage function relating global (or regional) changes in temperature with effects on human welfare via ecological changes. Changes in nonmarket goods and services can be valued using standard valuation tools in environmental economics such as travel-cost or hedonic approaches. For instance, studies of recreation in the United States suggest that outdoor recreation declines at higher temperatures, though with substantial opportunities for intraday substitution (Chan & Wichman 2020, Dundas & von Haefen 2020), while Kovacs et al. (2011) show persistent declines in property values near areas affected by mass tree mortality. Moore et al. (2022) estimate changes in species listing and spending under the Endangered Species Act due to climate change, bounding one aspect of climate change effects on extinction risk (i.e., increased conservation spending).

These kinds of empirical studies tend to be focused on limited geographic areas with large volumes of data, typically in a small number of wealthy countries. Because CO_2 is a global pollutant, SCC calculations require geographically comprehensive estimates of damages. Only a few comprehensive global damage functions for the ecological impacts of climate change exist, mostly associated with the FUND IAM (Anthoff & Tol 2014, Tol 2002). As discussed in Section 1, FUND includes damage functions for 12 types of climate change impacts, including two related to natural capital: a reduction in ecosystem services from wetlands due to sea-level rise, based on a meta-analysis of ecosystem service valuations of wetlands by Brander et al. (2006), and an ecosystems damage function capturing nonuse values of biodiversity decline.

Brooks & Newbold (2014) present a revised biodiversity loss damage function using updated ecological estimates of species loss with global warming, with valuation based on a stated-preference study (Kramer & Mercer 1997) and a meta-analysis of stated willingness to pay estimates (Richardson & Loomis 2009). They find much larger welfare effects of biodiversity decline than currently included in FUND due to both higher projected effects of warming on biodiversity and an alternate biodiversity value function. Finally, Brander et al. (2012) also provide an ocean acidification damage function, based on a similar approach to the wetland damage function in FUND using a meta-analysis of published ecosystem service values, but this has not been implemented in IAMs or contributed to SCC calculations.

However, Fenichel et al. (2016b) point out that a full valuation of changes in natural capital depends on institutional arrangements that manage the stock and determine the economic and behavioral response of actors to climate change–induced shifts in ecosystem productivity. Because most ecosystem goods are either public goods or common pool resources, one cannot assume optimal management, as might hold under a privately owned resource (Fenichel & Abbott 2014). They give the example of an open access fishery where, because rents are competed away, no wealth is preserved in the fish stocks by long-term management institutions and, therefore, climate change can not affect the value of the natural capital stock. In contrast, climate-induced shifts in the distribution or productivity of nonopen-access fisheries will have implications for the natural capital stock but will depend on the interaction of biophysical changes with the management institutions and the price function (Fenichel et al. 2016b). Damage functions that incorporate these institutional and price effects are still missing from the literature.

One issue to consider in modeling the costs of climate change's ecological impacts is the degree to which temperature change is best thought of as affecting a stock of natural capital or a flow of ecosystem services. Damages to the natural capital stock permanently reduce the flow of ecosystem services unless the stock is restored, whereas damages to the flow of ecosystem services produce impacts contemporaneously but not in future years (see Dell et al. 2012 for a discussion related to market climate change impacts). Different types of ecological changes could best be considered as stock versus flow impacts: CO_2 fertilization affects the productivity of the existing forest stock, for example, and might best be considered a flow impact. In contrast, extinctions, forest dieback, and wetland loss have long-lived impacts on the flow of ecosystem services from ecological systems and might best be thought of as stock impacts. These could be explicitly modeled as impacts to a natural capital stock, as did Bastien-Olvera & Moore (2021), or parametrized as a more typical IAM damage function falling on contemporaneous production but calibrated using the present value of the stream of lost ecosystem services [as in the wetland damage function in FUND or in Brooks & Newbold (2014)].

To date, most of the literature has considered the direct welfare costs of climate change effects on natural systems, but there are likely to be indirect effects too. For instance, climate change will lower the productivity of agricultural production in many areas, possibly driving agricultural expansion into natural areas with associated loss of habitat and ecosystem services. Piontek et al. (2021) used a computable general equilibrium model combined with species-distribution modeling to estimate the magnitude of these indirect effects on bird species in Vietnam and Australia. They find the indirect effects in this setting to be small relative to the direct effects of climate change on species habitat. A fuller accounting might also consider loss of productive agricultural land due to sea-level rise, such as in low-lying river deltas.

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A final issue related to modeling climate change damages in SCC calculations relates to the question of adaptations that might limit the adverse consequences of climate change. In general, climate damages should be calculated net of adaptations, i.e., including both the residual damages from climate change after adaptation and the adaptation costs (Cropper & Oates 1992). For many sectors, both the benefits and costs of adaptation are borne by those making the decision, meaning there are no externalities to the decision and, barring other market failures, we would expect optimal levels of adaptation to happen privately or autonomously (Hertel & Lobell 2014, Mendelsohn 2000). Farmers facing increased drought or homeowners experiencing uncomfortably warm temperatures, for example, incur both the benefits and costs of adaptive actions such as installing irrigation or air conditioning. However, ecosystem damages are different in that many adaptations are public goods and will be undertaken by governments. Although there is currently substantial discussion about the role natural resource managers and conservation agencies might play in adapting to climate change (Bradford et al. 2018, Dudney et al. 2018, Tittensor et al. 2019), the aggregate costs and effectiveness of these actions—and therefore the net benefits of adaptation—are still not well quantified.

In understanding climate change damages, it is important to note that while climate change is becoming an increasingly powerful driving force of ecological change, other human-caused mechanisms of ecosystem degradation currently exert more pressure on natural systems (Venter et al. 2016). For instance, conversion of ecosystems to cropland, pastures, and rangelands has been the major factor behind biodiversity loss, habitat fragmentation, and disruption of water and nutrient cycles (Foley et al. 2005). In addition, resource extraction, invasive species, and pollution are direct driving forces that affect ecosystems (Brondizio et al. 2019). These other mechanisms are closely related with modes of economic production and environmental regulations and will coevolve with climate change impacts over the twenty-first century. A complete picture of climate damages on ecosystems and its consequences for human well-being must include these parallel but interrelated damage pathways.

CONCLUSION

Human well-being depends partly on functioning ecosystems that provide inputs to the production of market and nonmarket goods, as well as pure existence and bequest values. Climate change over the next decades and centuries will profoundly reshape natural systems by changing, and in many cases reducing or disrupting, the flow of these benefits. Understanding how these changes affect aggregate estimates of the climate change costs such as the SCC is complex. It requires not just projecting the biophysical and ecological changes projected with a warmer planet—an active area of work within ecology and where large uncertainties still remain—but also modeling the dependence of economic production and human welfare on these systems. Given the difficulty of estimating nonmarket and, particularly, nonuse values, this almost certainly presents even greater empirical and modeling challenges.

Exactly how natural capital enters into the production and utility function has potentially large implications for the welfare effects of ecological climate impacts. But many of these parameters are still not well understood, and these questions speak to long-standing and still unresolved debates within economics regarding the substitutability of resources, land, or natural capital more generally in the production of consumption goods and human welfare.

It is also important to note that climate change is only one of many threats to biodiversity and well-functioning ecosystems over the twenty-first century and beyond. Other externalities from economic activity such as habitat destruction, pollution, or overexploitation present larger threats to the natural capital stock than does climate change. These effects will interact with climate change to determine the trajectory of natural systems in the Anthropocene. Climate change damages on natural capital therefore also need to be situated in this larger context of other market failures and evolving governance structures.

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LITERATURE CITED

AghaKouchak A, Chiang F, Huning LS, Love CA, Mallakpour I, et al. 2020. Climate extremes and compound hazards in a warming world. *Annu. Rev. Earth Planet. Sci.* 48:519–48

Anderegg WRL, Trugman AT, Badgley G, Anderson CM, Bartuska A, et al. 2020. Climate-driven risks to the climate mitigation potential of forests. *Science* 368(6497):eaaz7005

Anderson LG, Seijo JC. 2010. *Bioeconomics of Fisheries Management*. Hoboken, NJ: John Wiley & Sons

Anthoff D, Emmerling J. 2019. Inequality and the social cost of carbon. *J. Assoc. Environ. Resour. Econ.* 6(2):243–73

Anthoff D, Tol RSJ. 2014. *The climate Framework for Uncertainty, Negotiation and Distribution (FUND), technical description, version 3.9*. **https://www.fund-model.org/files/documentation/Fund-3-9-Scientific-Documentation.pdf**

Anthoff D, Tol RSJ, Yohe GW. 2009. Risk aversion, time preference, and the social cost of carbon. *Environ. Res. Lett.* 4(2):024002

Antle JM, Stöckle CO. 2017. Climate impacts on agriculture: insights from agronomic-economic analysis. *Rev. Environ. Econ. Policy* 11(2):299–318

Arrow KJ, Dasgupta P, Goulder LH, Mumford KJ, Oleson K. 2012. Sustainability and the measurement of wealth. *Environ. Dev. Econ.* 17(3):317–53

Bastien-Olvera BA, Moore FC. 2021. Use and non-use value of nature and the social cost of carbon. *Nat. Sustain.* 4:101–8

Baumgärtner S, Klein AM, Thiel D, Winkler K. 2015. Ramsey discounting of ecosystem services. *Environ. Resour. Econ.* 61(2):273–96

Blanc E, Schlenker W. 2017. The use of panel models in assessments of climate impacts on agriculture. *Rev. Environ. Econ. Policy* 11(2):258–79

Bradford JB, Betancourt JL, Butterfield BJ, Munson SM, Wood TE. 2018. Anticipatory natural resource science and management for a changing future. *Front. Ecol. Environ.* 16(5):295–303

Brander LM, Florax RJGM, Vermaat JE. 2006. The empirics of wetland valuation: a comprehensive summary and a meta-analysis of the literature. *Environ. Resour. Econ.* 33(2):223–50

Brander LM, Rehdanz K, Tol RSJ, Van Beukering PJH. 2012. The economic impact of ocean acidification on coral reefs. *Clim. Change Econ.* 3(1):1250002

Brondizio ES, Settele J, Diaz S, Ngo HT, eds. 2019. *Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*. Bonn, Ger.: IPBES

Brooks WR, Newbold SC. 2014. An updated biodiversity nonuse value function for use in climate change integrated assessment models. *Ecol. Econ.* 105:342–49

Carleton TA, Hsiang SM. 2016. Social and economic impacts of climate. *Science* 353(6304):1112

Carter C, Cui X, Ghanem D, Mérel P. 2018. Identifying the economic impacts of climate change on agriculture. *Annu. Rev. Resour. Econ.* 10:361–80

Chan NW, Wichman CJ. 2020. Climate change and recreation: evidence from North American cycling. *Environ. Resour. Econ.* 76:119–51

Cheung WWL, Lam VWY, Sarmiento JL, Kearney K, Watson R, et al. 2009. Large-scale redistribution of maximum fisheries catch potential in the global ocean under climate change. *Glob. Change Biol.* 16(1):24–35

Cropper ML, Oates WE. 1992. Environmental economics: a survey. *J. Econ. Lit.* 30(2):675–740

Dai A. 2013. Increasing drought under global warming in observations and models. *Nat. Clim. Change* 3:52–58

Dasgupta P. 2001. *Human Well-Being and the Natural Environment*. Oxford, UK: Oxford Univ. Press

Dasgupta P. 2014. Measuring the wealth of nations. *Annu. Rev. Resour. Econ.* 6:17–31

Dasgupta P. 2021. *The economics of biodiversity: the Dasgupta review*. Indep. Rep., HM Treas., Gov. UK, London

Dasgupta P, Mäler K-G. 2000. Net national product, wealth, and social well-being. *Environ. Dev. Econ.* 5(1):69–93

Dell BM, Jones BF, Olken BA. 2012. Temperature shocks and economic growth: evidence from the last half century. *Am. Econ. J. Macroecon.* 4(3):66–95

Dell M, Jones BF, Olken BA. 2014. What do we learn from the weather? The new climate-economy literature. *J. Econ. Lit.* 52(3):740–98

Dennig F, Budolfson MB, Fleurbaey M, Siebert A, Socolow RH. 2015. Inequality, climate impacts on the future poor, and carbon prices. *PNAS* 112(52):1513967112

Diaz D, Moore FC. 2017. Quantifying the economic risks of climate change. *Nat. Clim. Change* 7:774–82

Dietz S, van der Ploeg F, Rezai A, Venmans F. 2021. Are economists getting climate dynamics right and does it matter? *J. Assoc. Environ. Resour. Econ.* 8(5):895–921

Diffenbaugh NS, Swain DL, Touma D. 2015. Anthropogenic warming has increased drought risk in California. *PNAS* 112(13):3931–36

Drupp MA. 2018. Limits to substitution between ecosystem services and manufactured goods and implications for social discounting. *Environ. Resour. Econ.* 69:135–58

Drupp MA, Hänsel MC. 2020. Relative prices and climate policy: how the scarcity of non-market goods drives policy evaluation. *Am. Econ. J. Econ. Policy* 13:168–201

Dudney J, Hobbs RJ, Heilmayr R, Battles JJ, Suding KN. 2018. Navigating novelty and risk in resilience management. *Trends Ecol. Evol.* 33(11):863–73

Dudney J, Willing CE, Das AJ, Latimer AM, Nesmith JCB, Battles JJ. 2021. Nonlinear shifts in infectious rust disease due to climate change. *Nat. Commun.* 12:5102

Dundas SJ, von Haefen RH. 2020. The effects of weather on recreational fishing demand and adaptation: implications for a changing climate. *J. Assoc. Environ. Resour. Econ.* 7(2):209–42

Ebert U. 2003. Environmental goods and the distribution of income. *Environ. Resour. Econ.* 25(4):435–59

Fenichel EP, Abbott JK. 2014. Natural capital: from metaphor to measurement. *J. Assoc. Environ. Resour. Econ.* 1(1/2):1–27

Fenichel EP, Abbott JK, Bayham J, Boone W, Haacker EMK, Pfeiffer L. 2016a. Measuring the value of groundwater and other forms of natural capital. *PNAS* 113(9):2382–87

Fenichel EP, Levin SA, McCay B, St. Martin K, Abbott JK, Pinsky ML. 2016b. Wealth reallocation and sustainability under climate change. *Nat. Clim. Change* 6(3):237–44

Foley JA, DeFries R, Asner GP, Barford C, Bonan G, et al. 2005. Global consequences of land use. *Science* 309(5734):570–74

Friedlingstein P, O'Sullivan M, Jones MW, Andrew RM, Hauck J, et al. 2020. Global carbon budget 2020. *Earth Syst. Sci. Data* 12(4):3269–3340

Gaffney M. 2008. Keeping land in capital theory: Ricardo, Faustmann, Wicksell, and George. *Am. J. Econ. Sociol.* 67(1):119–41

Hackett SB, Moxnes E. 2015. Natural capital in integrated assessment models of climate change. *Ecol. Econ.* 116:354–61

Hamilton K, Clemens M. 1999. Genuine savings rates in developing countries. *World Bank Econ. Rev.* 13(2):333–56

Hamilton K, Hartwick J. 2014. Wealth and sustainability. *Oxford Rev. Econ. Policy* 30(1):170–87

Hertel TW, Lobell DB. 2014. Agricultural adaptation to climate change in rich and poor countries: Current modeling practice and potential for empirical contributions. *Energy Econ.* 46:562–75

Hertel TW, Rosch SD. 2010. Climate change, agriculture, and poverty. *Appl. Econ. Perspect. Policy* 32(3):355–85
Hoel M, Sterner T. 2007. Discounting and relative prices. *Clim. Change* 84(3–4):265–80
Hope CW. 2011. *The PAGE09 integrated assessment model: a technical description*. Work. Pap. 4/2011, Univ. Cambridge Judge Bus. Sch., Cambridge, UK. **https://www.jbs.cam.ac.uk/wp-content/uploads/2020/08/wp1104.pdf**
Howard PH, Sterner T. 2017. Few and not so far between: a meta-analysis of climate damage estimates. *Environ. Resour. Econ.* 68(1):197–225
Hsiang S, Kopp R, Jina A, Rising J, Delgado M, et al. 2017. Estimating economic damage from climate change in the United States. *Science* 356:1362–69
Hubau W, Lewis SL, Phillips OL, Affum-Baffoe K, Beeckman H, et al. 2020. Asynchronous carbon sink saturation in African and Amazonian tropical forests. *Nature* 579(7797):80–87
Hughes TP. 2003. Climate change, human impacts, and the resilience of coral reefs. *Science* 301(5635):929–33
Johnson JA, Ruta G, Baldos U, Cervigni R, Chonabayashi S, et al. 2021. *The economic case for nature: a global earth-economy model to assess development policy pathways*. Rep., World Bank Group, Washington, DC
Jones GP, McCormick MI, Srinivasan M, Eagle JV. 2004. Coral decline threatens fish biodiversity in marine reserves. *PNAS* 101(21):8251–53
Kikstra JS, Waidelich P, Rising J, Yumashev D, Hope C, et al. 2021. The social cost of carbon dioxide under climate-economy feedbacks and temperature variability. *Environ. Res. Lett.* 16:094037
Kopp RE, Golub A, Keohane N, Onda C. 2012. The influence of the specification of climate change damages on the social cost of carbon. *Economics* 6(1):2012–13
Kovacs K, Holmes TP, Englin JE, Alexander J. 2011. The dynamic response of housing values to a forest invasive disease: evidence from a sudden oak death infestation. *Environ. Resour. Econ.* 49(3):445–71
Kramer RA, Mercer DE. 1997. Valuing a global environmental good: U.S. residents' willingness to pay to protect tropical rain forests. *Land Econ.* 73(2):196–210
Krutilla JV. 1967. Conservation reconsidered. *Am. Econ. Rev.* 57(4):777–86
Lange G-M, Wodon Q, Carey K. 2018. *The Changing Wealth of Nations 2018: Building a Sustainable Future*. Washington, DC: World Bank
Liang Y, Rudik I, Zou E. 2021. *Economic production and biodiversity in the United States*. NBER Work. Pap. 29357
Maher SM, Fenichel EP, Schmitz OJ, Adamowicz WL. 2020. The economics of conservation debt: a natural capital approach to revealed valuation of ecological dynamics. *Ecol. Appl.* 30(6):e02132
Managi S, Kumar P. 2018. *Inclusive Wealth Report 2018: Measuring Progress Towards Sustainability*. New York: Routledge
Meadows DH, Randers J, Meadows DL. 1972. *The Limits to Growth: A Report for the Club of Rome's Project on the Predicament of Mankind*. New York: Universe Books
Mendelsohn R. 2000. Efficient adaptation to climate change. *Clim. Change* 45:583–600
Moore FC, Diaz DB. 2015. Temperature impacts on economic growth warrant stringent mitigation policy. *Nat. Clim. Change* 5:127–31
Moore FC, Stokes A, Conte M, Dong X. 2022. Noah's Ark in a warming world: climate change, biodiversity loss and public adaptation costs in the United States. *J. Assoc. Environ. Resour. Econ.* In press. **https://doi.org/10.1086/716662**
Nordhaus WD. 1992. An optimal transition path for controlling greenhouse gases. *Science* 258(5086):1315–19
Nordhaus WD. 2007. Critical assumptions in the Stern Review on climate change. *Science* 317:201–2
Nordhaus WD. 2017. Revisiting the social cost of carbon. *PNAS* 114(7):1518–23
Nordhaus WD, Moffat A. 2017. *A survey of global impacts of climate change: replication, survey methods, and a statistical analysis*. NBER Work. Pap. 23646
Pearce D. 1993. *Economic Values and the Natural World*. London: Earthscan
Pearce D, Atkinson GD. 1993. Capital theory and the measurement of sustainable development: an indicator of "weak" sustainability. *Ecol. Econ.* 8(2):103–8
Piontek F, Drouet L, Emmerling J, Kompas T, Méjean A, et al. 2021. Integrated perspective on translating biophysical to economic impacts of climate change. *Nat. Clim. Change* 11(7):563–72
Richardson L, Loomis JB. 2009. The total economic value of threatened, endangered and rare species: an updated meta-analysis. *Ecol. Econ.* 68(5):1535–48

Robinson R, Crick H, Learmonth J, Maclean I, Thomas C, et al. 2009. Travelling through a warming world: climate change and migratory species. *Endanger. Species Res.* 7(2):87–99

Rose SK, Diaz DB, Blanford GJ. 2017. Understanding the social cost of carbon: a model diagnostic and inter-comparison study. *Clim. Change Econ.* 8(2):1750009

Scholes JR, Betts R, Bunn S, Leadley R, Nepstad D, et al. 2014. Terrestrial and inland water systems. In *AR5 Climate Change 2014: Impacts, Adaptation, and Vulnerability. Working Group II Contribution to the IPCC 5th Assessment Report*, ed. CB Field, VR Barros, DJ Dokken, KJ Mach, M Mastrandrea, et al., pp. 271–359. Cambridge, UK/New York: Cambridge Univ. Press

Seidl R, Thom D, Kautz M, Martin-Benito D, Peltoniemi M, et al. 2017. Forest disturbances under climate change. *Nat. Clim. Change* 7(6):395–402

Siikamäki J, Santiago-Ávila FJ, Vail P. 2015. *Global assessment of non-wood forest ecosystem services*. Work. Pap., Prog. For., Washington, DC

Sitch S, Huntingford C, Gedney N, Levy PE, Lomas M, et al. 2008. Evaluation of the terrestrial carbon cycle, future plant geography and climate-carbon cycle feedbacks using five Dynamic Global Vegetation Models (DGVMs). *Glob. Change Biol.* 14(9):2015–39

Solow RM. 1956. A contribution to the theory of economic growth. *Q. J. Econ.* 70(1):65–94

Solow RM. 1974. The economics of resources or the resources of economics. *Am. Econ. Rev.* 64(2):1–14

Sterner T, Persson UM. 2008. An even sterner review: introducing relative prices into the discounting debate. *Rev. Environ. Econ. Policy* 2(1):61–76

Stiglitz J. 1974. Growth with exhaustible natural resources: efficient and optimal growth paths. *Rev. Econ. Stud.* 41:123–37

Tierney JE, Poulsen CJ, Montañez IP, Bhattacharya T, Feng R, et al. 2020. Past climates inform our future. *Science* 370(6517):680–89

Tittensor DP, Beger M, Boerder K, Boyce DG, Cavanagh RD, et al. 2019. Integrating climate adaptation and biodiversity conservation in the global ocean. *Sci. Adv.* 5(11):eaay9969

Tol RSJ. 1994. The damage costs of climate change: a note on tangibles and intangibles, applied to DICE. *Energy Policy* 22(5):436–38

Tol RSJ. 2002. Estimates of the damage costs of climate change. Part I: benchmark estimates. *Environ. Resour. Econ.* 21:47–73

Touma D, Ashfaq M, Nayak MA, Kao S-C, Diffenbaugh NS. 2015. A multi-model and multi-index evaluation of drought characteristics in the 21st century. *J. Hydrol.* 526:196–207

Turner BL, Matson PA, McCarthy JJ, Corell RW, Christensen L, et al. 2003. Illustrating the coupled human-environment system for vulnerability analysis: three case studies. *PNAS* 100(14):8080–85

Urban MC. 2015. Accelerating extinction risk from climate change. *Science* 348(6234):571–73

van der Ploeg S, De Groot R. 2010. *The TEEB Valuation Database: A Searchable Database of 1310 Estimates of Monetary Values of Ecosystem Services*. Wageningen, Neth.: Found. Sustain. Dev. **https://www.cbd.int/financial/gmr/teeb-database.xls**

Venter O, Sanderson EW, Magrach A, Allan JR, Beher J, et al. 2016. Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. *Nat. Commun.* 7(1):12558

Weitzman ML. 2012. What is the "damages function" for global warming—and what difference might it make? *Clim. Change Econ.* 1:57–69

Wiens JA, Stralberg D, Jongsomjit D, Howell CA, Snyder MA. 2009. Niches, models, and climate change: assessing the assumptions and uncertainties. *PNAS* 106 (Suppl. 2):19729–36

World Bank. 2006. *Where is the Wealth Of Nations? Measuring Capital for the 21st Century*. Washington, DC: World Bank

World Bank. 2011. *The Changing Wealth Of Nations: Measuring Sustainable Development in the New Millennium*. Washington, DC: World Bank

Zscheischler J, Martius O, Westra S, Bevacqua E, Raymond C, et al. 2020. A typology of compound weather and climate events. *Nat. Rev. Earth Environ.* 1(7):333–47

Chapter 1

Use and non-use value of nature and the social cost of carbon

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Use and non-use value of nature and the social cost of carbon

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Climate change is damaging ecosystems throughout the world with serious implications for human well-being. Quantifying the benefits of reducing emissions requires understanding these costs, but the unique and non-market nature of many goods provided by natural systems makes them difficult to value. Detailed representation of ecological damages in models used to calculate the costs of greenhouse gas emissions has been largely lacking. Here, we have expanded a cost–benefit integrated assessment model to include natural capital as a form of wealth. This brings benefits to people through non-use existence value and as an input into the production of ecosystem services and market goods. In our model, using central estimates for all parameters, optimal emissions reach zero by the year 2050, limiting warming to 1.5 °C by the year 2100. We used Monte Carlo analysis to examine the influence of several key uncertain model parameters, and examined the effect of adaptive investments in natural systems that partially offset climate damages. Overall, we show that accounting for the use and non-use value of nature has large implications for climate policy. Our analysis suggests that better understanding climate impacts on natural systems and associated welfare effects should be a high priority for future research.

Humans derive value from nature in multiple ways[1], which can be broadly categorized into use and non-use values[2,3]. Use values arise from the input of natural systems into economic activity, such as the flood-protection benefit mangroves provide to coastal cities or the raw materials used in producing market goods[4]. Non-use values instead arise directly from the existence of natural systems and species even in the absence of any direct use or consumption. Principal non-use values are existence value (knowledge that certain species or ecosystems exist) and bequest value (the ability of future generations to derive welfare from natural systems)[3,5].

Climate change is already having a discernible influence on ecosystem functioning, an effect that will continue to grow throughout the twenty-first century[6–12]. These changes will affect human well-being both through the disruption of ecosystem services and the direct and permanent loss of non-use value from extinctions and ecosystem degradation[13,14]. The unique characteristics of some benefits derived from ecosystems make them only imperfectly substitutable with other forms of consumption that contribute to welfare[15], and previous work has suggested that accounting for this imperfect substitutability may substantially increase estimates of the welfare costs of climate change[16–20]. In addition, any damage to the stock of natural capital would permanently reduce the flow of benefits from natural systems, meaning that costs arising from the ecological effects of climate change would be long-lived and cumulative[21].

Cost–benefit integrated assessment models represent interactions between the economy and climate, capturing trade-offs between the costs of reducing greenhouse gas emissions and the benefits of avoided climate change. These models calculate the social cost of carbon (SCC), an estimate of the net present value of a marginal ton of CO_2 emissions used in the cost–benefit analysis of climate and energy policy. The SCC should include a comprehensive accounting of impacts, including both effects on market sectors (which can be largely captured by standard economic indicators, such as gross domestic product (GDP)) as well as extra-market damages, such as changes to mortality and effects on natural systems[22,23]. Standard estimates of the SCC, however, include only a rough accounting of ecological damages and do not model either the imperfect substitutability of natural capital and ecosystem services or the potentially permanent loss of welfare associated with damages to the stock of natural capital[23]. These estimates may, therefore, be missing characteristics essential for assessing the welfare costs of anthropogenic climate change, something that was noted decades ago[24] but has not been widely implemented in the cost–benefit analysis of climate policy.

In this study we expanded the 2013R version of the Dynamic Integrated model of Climate and the Economy (DICE)[25] to represent the unique nature of climate change impacts on natural systems. In particular, we adopt the concept of comprehensive wealth widely developed in the sustainability literature[26–28], which includes natural capital as an input to production[28] in addition to the more standard manufactured capital and human capital. We modelled three pathways by which the stock of natural capital supports human welfare (Fig. 1):

- As a relatively minor input to the production of most market goods (orange arrows, Fig. 1)
- As a more important input to the production of ecosystem goods and services (green arrows, Fig. 1)
- As the source of non-use goods associated with existence and bequest values (blue arrows, Fig. 1)

We modelled the imperfect substitutability of these three types of goods in the social welfare function using a nested constant elasticity of substitution (CES) utility function. This functional form allows the two types of use-value outputs (economic output and ecosystem services) to be relatively close substitutes compared with the substitutability between non-use value and the bundle of use values (Methods). Additionally, we added a damage function that allows climate change to affect the stock of natural capital

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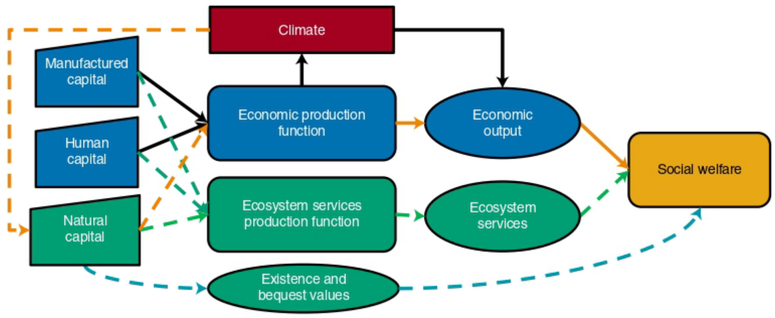

Fig. 1 | GreenDICE diagram for modelling the welfare effects of climate change impacts on natural capital. Schematic of the GreenDICE structure showing the instrumental (green and orange arrows) and intrinsic (blue arrows) pathways through which natural capital affects welfare. Dashed links represent additions to the standard DICE model. Solid black lines show relationships already present in DICE.

directly. We call this model with modified capital, production, utility and damages the GreenDICE model. Detailed equations and calibration parameters relevant to GreeenDICE are given in the Methods section.

We present here versions of the full GreenDICE model that gradually add these pathways to the standard DICE model in order to attribute damages to specific pathways. The first change to DICE involves including natural capital in the economic production function, allowing it to influence social welfare through the consumption of market goods. We call this the 'Market Only' specification (orange arrows, Fig. 1). The next specification is a complete representation of use values, where the production of ecosystem services is captured using a second production function that relies more heavily on natural than manufactured capital. Ecosystem services also enter into the utility function, contributing to welfare in a way that is only imperfectly substitutable with standard market goods. We call this the 'All Use Values' specification (orange and green arrows, Fig. 1). Finally, the complete specification also includes non-use values that arise directly from the natural capital stock and are again imperfectly substitutable with the bundle of use values, becoming a nested CES utility function. The full model, which includes all use and non-use values, is referred to simply as 'GreenDICE' (orange, green and blue arrows, Fig. 1).

Although previous work has revealed the importance of substitutability between environmental goods, broadly defined, and manufactured goods[17–19], a key advance here is in explicitly modelling the production of these goods from natural capital stock, including the potential for climate damages to affect this stock. This allows the possibility to distinguish between two primary pathways by which changes in natural capital affect welfare: those that operate through production, affecting use values, and those that arise directly from changes in the natural capital stock, affecting non-use values. This also distinguishes this model from previous work that incorporated natural capital into DICE[29], in which the costs of ecosystem degradation due to both climate and non-climate factors were modelled, but not the direct role of natural capital in production or the imperfectly substitutable nature of environmental goods. A final important distinction from previous work relates to the dynamics of damages. By explicitly modelling damages to the natural capital stock, the model allows impacts to be persistent and cumulative, because losses to natural capital can affect welfare in future time periods. Persistence is an important but poorly constrained determinant of total climate damages, and this modelling framework relaxes some of the constraints of the standard DICE model, in which damages only affect output and are therefore mostly non-persistent[21,30].

One important note is that ecosystem services should be understood here to exclude the carbon sequestration value of natural systems. Although this is an important component of ecosystem services, it should be represented explicitly in the DICE model as part of the carbon cycle, because changes to the land or ocean carbon sink will affect the social cost of carbon by altering the relationship between emissions and temperature. As has been pointed out in previous work[31], the carbon cycle model in DICE is very simple, omitting any feedbacks or direct representation of the land carbon sink. Modifying the DICE carbon cycle model is beyond the scope of this paper, so we simply note that the interpretation of ecosystem services represented here excludes carbon sequestration and instead captures other use values, such as recreation and aesthetic enjoyment, nutrient cycling and the provision of other extra-market goods and services.

Results

Figure 2 shows the trajectories of emissions that maximize welfare in the model with their corresponding temperature rise and the optimal carbon tax (SCC under welfare-maximizing conditions). We ran the model under standard DICE specifications and with the different specifications of GreenDICE. The introduction of additional damage pathways resulting from damages to natural capital increases the costs of climate change, raising the optimal carbon tax in 2020 (Fig. 2a), lowering welfare-maximizing emissions (Fig. 2b), resulting in lower global temperatures throughout the twenty-first century (Fig. 2c). Damages to natural capital reduce economic production (Market Only specification) and have a large effect compared with the standard DICE specification, limiting the temperature increase to 2 °C by the end of the century. Incorporating the relatively more important role of natural capital in producing ecosystem goods and services (All Use Values specification) has an additional effect, raising the optimal carbon tax in 2020 to US\$133 per ton CO_2 from US\$72 in the Market Only specification.

Adding non-use values to the full GreenDICE model (GreenDICE specification, Fig. 2) further increases welfare losses arising from damages to the natural capital stock. These losses, only imperfectly substitutable with consumption goods, increase the optimal carbon tax in 2020 to US\$160 per ton CO_2, more than five times higher than the standard DICE model (US\$28 per ton in 2020). Emissions decline rapidly, reaching zero by 2050 and limiting warming to 1.5 °C by the end of the century.

Many of the parameters relating to production, utility and damages introduced into GreenDICE are both uncertain and extremely challenging to measure directly. This is particularly the case for

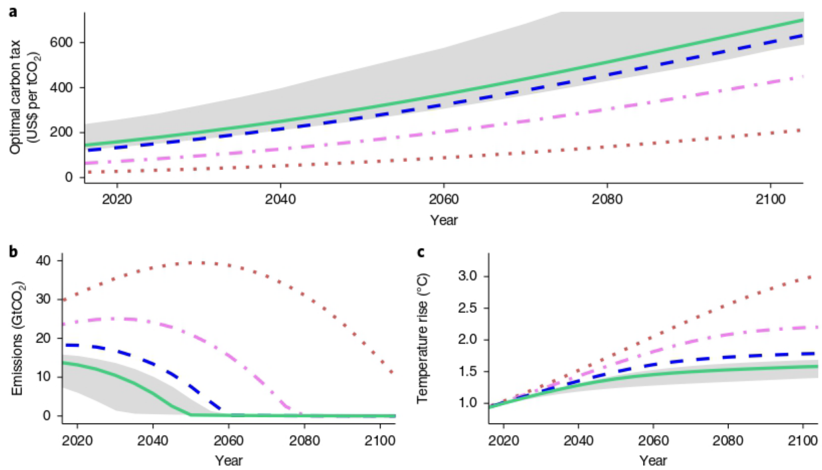

Fig. 2 | Climate policy results derived from the DICE and GreenDICE models. Key climate policy variables in the twenty-first century based on the standard DICE model (dotted line), Market Only specification of GreenDICE (dot-dashed line), All Use Values specification of GreenDICE (dashed line) and the complete specification of GreenDICE (solid line). The shaded areas show the interquartile spread of outcomes based on a Monte Carlo simulation of the eight parameters introduced into GreenDICE. **a–c**, The optimal carbon tax shown in US$$_{2019}$ per ton CO_2 (**a**), CO_2 emissions (**b**) and rise in global mean surface temperature above pre-industrial temperature (**c**).

the parameterization of non-use values in the utility function (through the parameters s_2 and γ_4, Supplementary Table 1), the magnitudes of which are debated within economics[32–34]. Moreover, there is no consensus on how to accurately measure these values, particularly at the high level of aggregation required to inform a model like GreenDICE. The values of these parameters are therefore not well supported empirically (Supplementary Table 1), so understanding their role in determining findings is important. We achieved this through an extensive exploration of the uncertain parameter space in both a one-at-a-time sensitivity analysis and a full Monte Carlo analysis.

We first performed a one-at-a-time sensitivity analysis of the full GreenDICE specification to compare the implications of uncertainty on key policy variables (details and uncertainty ranges are given in Supplementary Table 1). Figure 3 shows the effects of such parameters on the optimal carbon tax in 2020 and the global mean surface temperature in 2100 under welfare maximization conditions. The sensitivity to three widely studied parameters, the pure rate of time preference, the climate sensitivity and the relative risk aversion, are also provided for comparison.

Figure 3 shows the expected and well-understood sensitivity to the pure rate of time preference for values of 0.1, 1.5 and 3% (ref. [35]). Important policy variables are generally less sensitive to variation in the GreenDICE parameters. The three variables with the largest impact are the natural capital-adjusted total factor productivity (which partly determines the output elasticity with respect to natural capital; Supplementary Information), the elasticity of non-use values with respect to natural capital and the magnitude of climate change impacts on natural capital (damage to natural capital). If impacts to the natural system are larger than our central estimate or if natural capital plays a more important role in welfare than in our main specification, substantially more stringent climate policy could be warranted, including the stabilization of global temperatures well below 1.5 °C above pre-industrial temperatures. However, even given the uncertainty of key parameters, GreenDICE specifications consistently produce a larger optimal carbon tax in 2020 and, correspondingly, lower temperatures in 2100 than the standard DICE model (dashed line, Fig. 3).

The one-at-a-time sensitivity analysis might overlook important interactions among parameters. For example, a large role of natural capital in economic production combined with large damages to natural capital might imply much larger damages than from high values of either parameter alone. To shed light on these interaction effects, we performed a Monte Carlo analysis, sampling 1,000 times from all GreenDICE parameters and optimizing the model under the sampled parameters. To understand the factors and interactions driving variation in two key policy variables (the optimal carbon tax in 2020 and temperature in 2100), we fitted a random forest on the Monte Carlo analysis output[36]. This procedure creates 500 regression trees that sequentially partition the data to maximize the variance in the output variable explained by the partitions (Methods). The earlier in the regression tree a particular parameter appears, the more important it is in explaining the variation in policy variables from the Monte Carlo analysis[37].

Figure 4 shows the mean minimum depth for each variable in all 500 regression trees in the random forest. This clearly shows that the magnitude of climate change impacts on natural capital (damage to natural capital) has a dominating influence in determining the optimal carbon tax in 2020: it was always chosen as the first or second variable in the regression trees. Two other key variables are those that together determine the role of natural capital in production (natural capital-adjusted total factor productivity and the initial stock of natural capital; Supplementary Information). Additionally, the substitutability between welfare from use and non-use goods in the utility function proves important and has previously been identified as a critical parameter by other researchers in simpler models[17,19].

The interaction between important variables identified through the Monte Carlo analysis, namely the initial natural capital stock and the natural capital-adjusted total factor productivity, has been explored in more detail and the results are presented in Extended Data Fig. 1. The costs of ecological damages are much higher if the

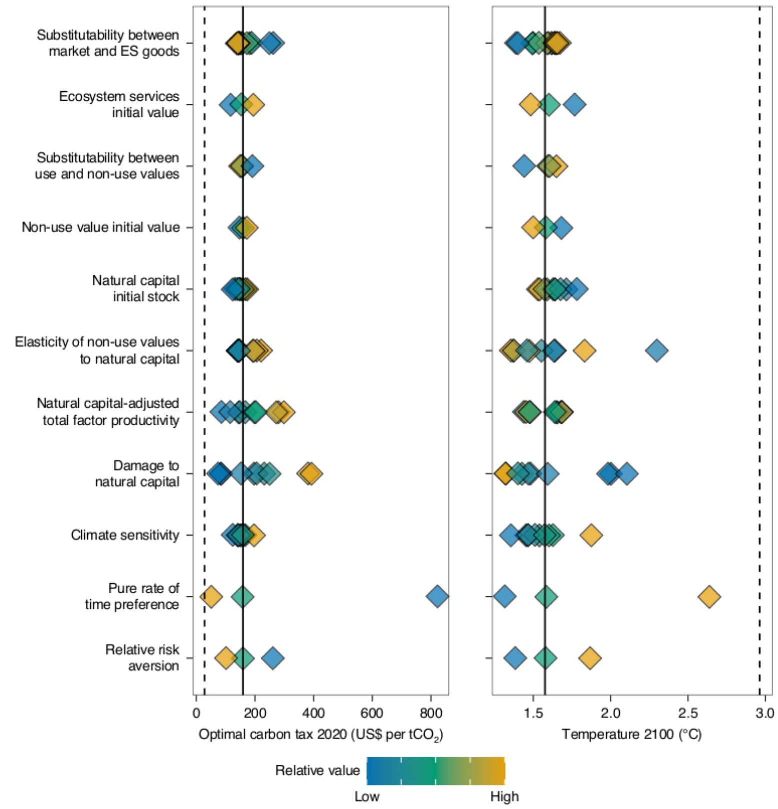

Fig. 3 | Sensitivity analysis of uncertain parameters under welfare maximization conditions. Sensitivity analysis of key uncertain parameters in GreenDICE. ES, ecosystem services. The colour gradient indicates the scaled parameter range between low (blue) and high (yellow) values. The vertical lines indicate the preferred GreenDICE (solid) and standard DICE (dashed) estimates. The [min,max] ranges of the values from top to bottom are as follows: θ_1: [−0.016,0.86]; s_1: [0.05,0.15]; θ_2: [0.27,0.78]; s_2: [0.05,0.15]; N_0:[$0.147K_0$, $0.912K_0$]; γ_4: [0.2,0.8]; atfp: [1.00065,1.043683]; a_n: [0,0.0806]; cs: [2.268,3.499]; prtp: [0.001,0.03]; α: [1.08,1.82]. More information on the parameters can be found in the Methods and the rationale for the ranges is provided in the Supplementary Information.

natural capital initial stock is large and plays an important role in production. Comprehensive wealth accounting in different countries shows that these conditions are most prevalent in developing economies. In particular, in poorer countries, natural capital tends to be large relative to both manufactured and human capital[28]. Thus, although GreenDICE does not explicitly model regional heterogeneity, results suggest that ecological damages may be disproportionately concentrated in developing countries.

It is important to note that both the Monte Carlo analysis and the sensitivity analysis explore the variation in model runs optimized given particular values of the uncertain parameters. The results, therefore, show the sensitivity of optimal mitigation pathways to different uncertain parameters. This is different from the single mitigation pathway that would be optimal given this uncertainty space, which has been explored in recent papers that implement dynamic stochastic versions of the DICE model that help to avoid potential policy inconsistencies[38–41]. The additional state variables in the GreenDICE model, as well as the large number of uncertain parameters, mean that a dynamic stochastic implementation is computationally challenging and beyond the scope of this paper. Therefore we simply note that the interpretation of uncertainty and optimal control explored here differs conceptually from that addressed in the growing literature on dynamic stochastic integrated assessment models.

Finally, we also explored the role of adaptive investments in alleviating the costs of ecological damages from climate change. In the standard DICE model, production can be invested either in capital for future production or in greenhouse gas mitigation, with the remainder contributing to utility through consumption. We added an additional savings pathway to GreenDICE, allowing production to also be used to offset the damages to natural capital from climate change (called the Adaptive Investments model). This is a highly stylized representation of adaptive spending for ecological systems that could include protection of habitat, managed relocation of species and increased conservation spending to prevent extinction. GreenDICE was re-optimized with this additional savings pathway as a third control variable. Calibration and details of implementation are given in the Methods section with the sensitivity to parameterizations of the cost function given in Extended Data Fig. 2.

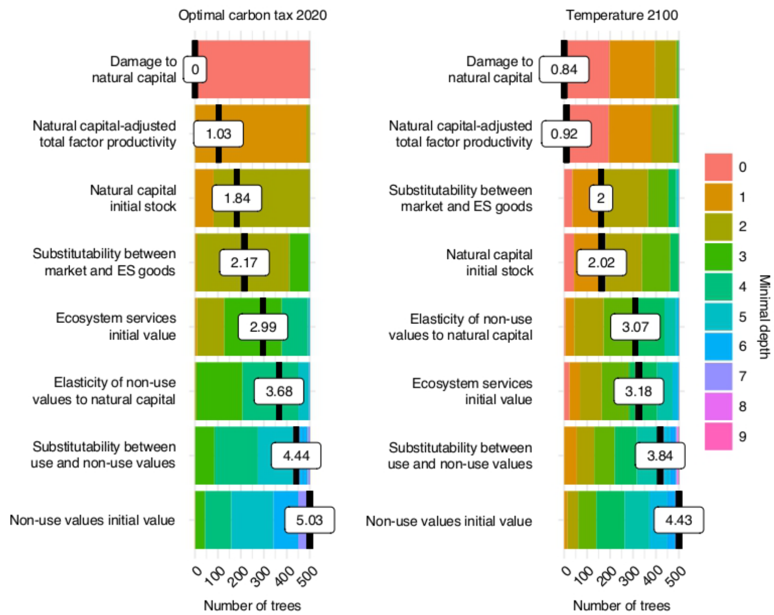

Fig. 4 | Random forest analysis of Monte Carlo simulation. Minimal depth at which each parameter is found in each tree of the random forest, predicting the social cost of carbon in 2020 (left) and temperature in 2100 (right) based on Monte Carlo simulations. A lower minimal depth indicates that the parameter has more importance in explaining variation in the variable of interest.

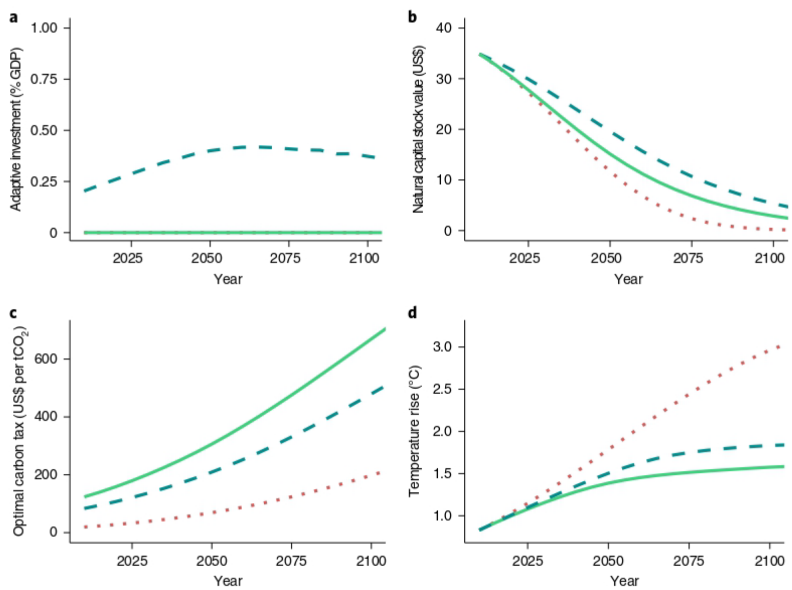

Fig. 5 | Impacts of the Adaptive Investments model on natural capital and climate damage. a–d, Effects of the Adaptive Investments model (dashed line) on investments in adaptation (**a**), natural capital stock (**b**), the optimal carbon tax (**c**) and rise in temperature (**d**) compared with the standard DICE model (dotted line) and GreenDICE (solid line) .

Figure 5 shows the results from implementing this additional savings pathway, comparing the investments in natural capital, natural capital stock, the optimal carbon tax and global temperatures with both DICE and GreenDICE. The Adaptive Investments model reduces temperature impacts and produces a constant stream of investments just above 0.25% of gross world product (GWP) throughout the century in the preferred parameterization of the cost function[42]. In the model, these investments are able to partially offset ecological climate damages, producing an optimal carbon tax lower than GreenDICE and allowing for a slightly higher temperature at the end of the century. This result points to the importance of adaptation in determining climate change damages, something emphasized in previous studies[43,44]. However, the question of how much protecting natural systems from climate change would cost and exactly how effective that spending would be at reducing the welfare costs of ecological impacts is highly uncertain.

Discussion

In Extended Data Fig. 3 we also show the results from an alternative implementation of savings that allows output to be invested directly in natural capital, in the same way that output is invested in manufactured capital in the standard DICE model. This is a highly aggregate representation of spending to restore, expand and improve natural systems, for instance, through the expansion of protected areas and managed restoration efforts not necessarily tied to climate change damages as in the Adaptive Investments implementation shown in Fig. 5.

Extended Data Fig. 3 shows that allowing this direct investment leads to very large initial investments in natural capital that greatly increase the existing natural capital stock. This behaviour suggests that the level of natural capital in GreenDICE is lower than that which would maximize welfare in the model, because relaxing the constraint on the level of natural capital produces much larger stocks. Parameterizations of the initial natural capital stock are taken from estimates from the literature on comprehensive wealth accounting (Methods), suggesting either that the importance of natural capital in utility is over-estimated in GreenDICE or that current stocks of natural capital are far below optimal levels. Given that many of the benefits provided by ecosystems are public goods, which are notoriously difficult to provide optimally, it would not be surprising if natural capital today were, in fact, lower than welfare-maximizing levels. However, we note that this modelling abstracts away from real dynamic constraints that limit the rate at which economic output can be converted into natural capital, and these results should therefore be understood as illustrative only.

Natural systems support human welfare through a variety of pathways. Because these systems are thought to be particularly vulnerable to climate change impacts, and because natural capital and the goods it provides are only partially substitutable with either other forms of capital or other consumption goods, explicitly modelling the macroeconomic role of natural capital is important to accurately estimate the effects of climate change on human well-being. Failing to acknowledge nature's unique contributions to social welfare through use and non-use values, and the threats posed by climate change to natural systems, risks substantially underestimating the costs of climate change.

Parameterization of GreenDICE has been informed by a number of existing studies estimating the importance of natural capital in economic production (Methods and Supplementary Table 1). However, both the magnitude and uncertainty of impacts demonstrated here point to the need for more work to improve the precision of these parameter estimates. The GreenDICE parameter identified as the most important in the Monte Carlo analysis was the damage function parameter that relates changes in climate to impacts on natural systems (Fig. 4). Therefore, integrating current knowledge from ecology on the risks climate change poses to the provision of ecosystem services and biodiversity[45] could substantially improve confidence in the effects reported here, although gaps in the scientific understanding of the response of natural systems to climate change, including potential thresholds and tipping points, remain.

In addition, versions of the model that allow for adaptive investments in natural capital (Fig. 5) show the interaction between adaptation and mitigation investments, which act here as substitutes. Better quantifying the costs and benefits of these adaptive investments would help constrain this effect. Important future steps involve developing a regional model to explore heterogeneity in the importance of natural capital for human welfare in different countries to explicitly model the distributional implications of ecological damages from climate change[46], analysing optimal climate policies under epistemic uncertainty using robust decision-making lenses and investigating the effects of including in this framework non-climate drivers of natural capital degradation.

Methods

We modified and extended the 2013R DICE model[25] using the Mimi Framework (https://www.mimiframework.org/), a Julia package for integrated assessment models[47,48]. We represented the use and non-use values of nature by untangling three different components of the utility function: 1) normal consumption goods, 2) ecosystem services (here defined as non-market goods heavily reliant on natural capital for production, such as recreation or cultural values) and 3) existence and bequest values. These goods are produced by different combinations of the three types of capital (manufactured, natural and human). Therefore, we modified the social welfare function in DICE to represent the components of social well-being and specified a function to represent the production function for each of these goods (Supplementary Table 6).

The social welfare function depends on two components. The first derivative is positive and the second derivative is negative with respect to both components (that is, it is increasing and quasi-concave in both components). The use value component ($\tilde{c_t}$) follows the structure proposed by Hoel and Sterner[16] and the work carried out by Drupp and Hänsel[18]. $\tilde{c_t}$ represents the level of current consumption per capita of a representative good at time t, and is composed of two imperfect substitutes: $\tilde{c_t} = \left[(1-s)c_t^{\theta} + se_t^{\theta}\right]^{1/\theta}$. The first element ($c$) is the consumption per capita of a comprehensive economic output and the second component (e) is the flow of a representative ecosystem service per capita, which captures the production of goods and services particularly reliant on natural systems (for example, recreation), except carbon sequestration, as DICE has a carbon cycle component that we leave unchanged because it is beyond the scope of this analysis. The parameter θ is the substitutability parameter and s represents the fraction of use values that we get from ecosystem services.

The non-use value component of the welfare function is simply represented by a flow of intangibles (i) that arise directly from natural capital (for example, existence value). Therefore, the overall representative flow of consumption (f) is derived from both use and non-use values that are imperfectly substitutable with each other, and follows a similar structure to above: $f_t = \left[\tilde{c_t}^{\theta_2} + s_2 i_t^{\theta_2}\right]^{1/\theta_2}$, where θ_2 is the substitutability parameter between use and non-use values and s_2 is a scaling parameter that transforms the flow of intangibles into a utility value. Welfare (W) is given by $W = \sum_{t=2020}^{2300} e^{-\rho t} u(f_t)$, where ρ is the pure rate of time preference and, following the standard DICE model, the utility function ($u(f)$) incorporates a constant relative risk aversion (α) and is given by $u(f) = \frac{f^{1-\alpha}}{(1-\alpha)}$.

The three production functions that underlie each component of f use the Cobb–Douglas form (Supplementary Table 6). The production of market goods (Y) is given by $Y = aL^{\gamma_1}K^{\gamma_2}N^{\gamma_3}$. This modifies the standard DICE representation of production by separating natural capital (N) from manufactured capital (K) as an input to production[49]. The elasticity of production (γ_1) with respect to labour (L) was kept at 0.7, as in standard DICE, whereas γ_2 (the elasticity of production with respect to manufactured capital) was adjusted to account for the natural capital input and the elasticity of production with respect to natural capital (γ_3)[50]. This adjustment was calibrated using World Bank estimates of the global value of natural capital[28] and Organisation for Economic Cooperation and Development estimates of the role of natural capital in determining total factor productivity (a) once natural capital is taken into account[51] (Supplementary Information). This substantially expands previous efforts to include natural capital in DICE. For example, Hackett and Moxnes[29] included natural capital damages as a separate impact on economic output. However, they did not include natural capital as part of the model of economic production, which better reflects recent literature on comprehensive wealth accounting[28,51].

Similarly, ecosystem services arise from the interaction of population (parameterized by labour L), manufactured capital and natural capital[2,52]. However, to our knowledge, there are no studies that have estimated the parameters of a highly aggregate ecosystem services production function on a global scale. The results of a recent fine-scale global study by Chaplin-Kramer et al.[46] indicate that nature's contributions to people arise when ecosystem processes interact with population, and that manufactured capital does not play an important role. Therefore, given the limited evidence available to constrain the parameters of this production function, we assume that the ecosystem services production function is $E = aL^{\gamma_1}K^{\gamma_3}N^{\gamma_2}$, where the elasticities of production with respect to manufactured and natural capital have been exchanged, representing the greater reliance of use ecosystem services on natural capital (given that $\gamma_2 \gg \gamma_3$ in the preferred parameterization).

Finally, we modelled the production of non-use values (i) as a function of natural capital only. This captures primarily existence values (the value of knowing that species or certain ecosystems exist)[32] and was therefore modelled as being produced exclusively from natural capital, without capital or labour inputs. Specifically, we set $i = N^{\gamma_4}$, assuming the contributions of people and manufactured capital to be negligible and $\gamma_4 = 0.5$ to represent diminishing marginal benefits. As with the ecosystem service production function, there is little empirical evidence to support this parameterization, but sensitivity to this parameter is explored in the sensitivity analysis.

To represent climate damage to natural systems, we added a second damage function that allows warming from climate change to affect the stock of natural capital. The damage parameter α of this damage function, $N_{t+1} = \frac{N_t}{1+\alpha T^2}$, was calibrated to reflect the non-market damages of temperature (T) originally embedded in the DICE damage function. We followed the Drupp and Hänsel[18] calibration of the damage parameter by matching the damage level of the DICE 2013R model as given by Nordhaus and Sztorc[25], using the database of damage estimates collected by Howard and Sterner[53] to separate market and non-market damages as well as using the results of Hsiang et al.[54] to control for mortality (Supplementary Information).

It is important to note that in GreenDICE, the climate is damaging the natural capital stock, which potentially causes persistent losses in welfare. In contrast, other well-known models[16,18] introduced the climate impacts directly into the ecosystem services, causing mostly non-persistent impacts on the levels of consumption (Supplementary Information). Although the contemporaneous effects of higher temperatures were calibrated to match the DICE damage function (Supplementary Information), allowing these to accrue to natural capital rather than the level of output means that these damages persist in GreenDICE differently than in standard DICE. This means that the effects of total damages on any given temperature trajectory will be higher in GreenDICE.

The implementation of investments in natural capital as a third control variable for welfare-maximizing policy was carried out in two ways. First, in the Adaptive Investments specification we allow investments (I_t) to reduce the natural capital damages (D_{Nt}) by a fraction ad_t, following the standard DICE functional form $N_{t+1} = N_t - D_{Nt}(1 - \mathrm{ad}_t)$, producing a convex cost function (I_t) similar to the emissions abatement cost function in DICE: $I_t = Y_t \mathrm{ad}_t^w$. The parameter w was calibrated assuming that investing 2.1% of annual GWP in environmental protection would reduce 50% of climate damages and was varied in a sensitivity analysis (Supplementary Information and Extended Data Fig. 2). An alternative form of investment (Asset Investment) was introduced by allowing spending to directly increase the natural capital stock. The costs of these investments were based on the asset pricing literature[55], where the price of a unit of natural capital at time t ($p_{N,t}$), relative to the price of a unit of manufactured capital at time t is given by $p_{N,t} = \frac{\partial W_t / \partial N_t}{\partial W_t / \partial K_t}$. The model iteratively maximizes welfare by investing in natural capital based on this asset price until convergence of prices and investment is reached (see the Results and Discussion in the Supplementary Information).

It is important to note that GreenDICE is based on DICE-2013R, not the more recent DICE-2016R2, which includes new projections of population, economic growth and carbon intensity and begins in 2015 instead of 2010. These changes could change the specific numbers in the results, such as the projected emissions, which would start closer to 2020, but are very unlikely to alter any conclusions. This is particularly true because many of the updates to specific parameters in DICE-2016R2 have already been included in our sensitivity analysis, for example, the damage function parameter and the climate sensitivity.

Data availability

Results of the simulations are available at https://github.com/BerBastien/GreenDICE/tree/master/Results

Code availability

GreenDICE code is available at www.GitHub.com/BerBastien/GreenDICE

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References

1. Pascual, U. et al. Valuing nature's contributions to people: the IPBES approach. *Curr. Opin. Environ. Sustain.* **26**, 7–16 (2017).
2. De Groot, R. S., Alkemade, R., Braat, L., Hein, L. & Willemen, L. Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. *Ecol. Complex.* **7**, 260–272 (2010).
3. Turner, R. K. et al. Valuing nature: lessons learned and future research directions. *Ecol. Econ.* **46**, 493–510 (2003).
4. Agarwala, M., Atkinson, G., Baldock, C. & Gardiner, B. Natural capital accounting and climate change. *Nat. Clim. Change* **4**, 520–522 (2014).
5. Jones-Walters, L. & Mulder, I. Valuing nature: the economics of biodiversity. *J. Nat. Conserv.* **17**, 245–247 (2009).
6. Gomes, V. H. F., Vieira, I. C. G., Salomão, R. P. & ter Steege, H. Amazonian tree species threatened by deforestation and climate change. *Nat. Clim. Change* **9**, 547–553 (2019).
7. Rogers, L. A. et al. Shifting habitats expose fishing communities to risk under climate change. *Nat. Clim. Change* **9**, 512–516 (2019).
8. Roberts, C. P., Allen, C. R., Angeler, D. G. & Twidwell, D. Shifting avian spatial regimes in a changing climate. *Nat. Clim. Change* **9**, 562–566 (2019).
9. Pecl, G. T. et al. Biodiversity redistribution under climate change: impacts on ecosystems and human well-being. *Science* **355**, eaai9214 (2017).
10. Settele, J. et al. in *Climate Change 2014: Impacts, Adaptation, and Vulnerability* (eds. Field, C. B. et al.) 271–360 (IPCC, Cambridge Univ. Press, 2015).
11. Warszawski, L. et al. A multi-model analysis of risk of ecosystem shifts under climate change. *Environ. Res. Lett.* **8**, 044018 (2013).
12. Parmesan, C. & Yohe, G. A globally coherent fingerprint of climate change impacts across natural systems. *Nature* **421**, 37–42 (2003).
13. *Global Assessment Report on Biodiversity and Ecosystem Services* (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, 2019).
14. Millennium Ecosystem Assessment *Ecosystems and Human Well-being: Synthesis* (Island Press, 2005).
15. Drupp, M. A. Limits to substitution between ecosystem services and manufactured goods and implications for social discounting. *Environ. Resour. Econ.* **69**, 135–158 (2018).
16. Hoel, M. & Sterner, T. Discounting and relative prices. *Clim. Change* **84**, 265–280 (2007).
17. Sterner, T. & Persson, U. M. An even sterner review: introducing relative prices into the discounting debate. *Rev. Environ. Econ. Policy* **2**, 61–76 (2008).
18. Drupp, M. A. & Hänsel, M. C. Relative prices and climate policy: how the scarcity of non-market goods drives policy evaluation. *Am. Econ. J. Econ. Policy* https://www.aeaweb.org/articles?id=10.1257/pol.20180760 (2020).
19. Tol, R. S. The damage costs of climate change: a note on tangibles and intangibles, applied to DICE. *Energy Policy* **22**, 436–438 (1994).
20. Kopp, R. E., Golub, A., Keohane, N. O. & Onda, C. The influence of the specification of climate change damages on the social cost of carbon. *Economics-Kiel* **6**, 1–40 (2012).
21. Moore, F. C. & Diaz, D. B. Temperature impacts on economic growth warrant stringent mitigation policy. *Nat. Clim. Change* **5**, 127–131 (2015).
22. Tol, R. S. Estimates of the damage costs of climate change. Part 1: benchmark estimates. *Environ. Resour. Econ.* **21**, 47–73 (2002).
23. Diaz, D. & Moore, F. Quantifying the economic risks of climate change. *Nat. Clim. Change* **7**, 774–782 (2017).
24. Nordhaus, W. D. & Tobin, J. in *Economic Research: Retrospect and Prospect* Vol. 5 1–80 (NBER, 1972).
25. Nordhaus, W. & Sztorc, P. *DICE 2013R: Introduction and User's Manual* (retrieved November, 2019); https://go.nature.com/3kmwMc5
26. Barbier, E. B. The concept of natural capital. *Oxf. Rev. Econ. Policy* **35**, 14–36 (2019).
27. Arrow, K. J., Dasgupta, P., Goulder, L. H., Mumford, K. J. & Oleson, K. Sustainability and the measurement of wealth. *Environ. Dev. Econ.* **17**, 317–353 (2012).
28. Lange, G.-M., Wodon, Q. & Carey, K. *The Changing Wealth of Nations 2018: Building a Sustainable Future* (The World Bank, 2018).
29. Hackett, S. B. & Moxnes, E. Natural capital in integrated assessment models of climate change. *Ecol. Econ.* **116**, 354–361 (2015).
30. Dietz, S. & Stern, N. Endogenous growth, convexity of damage and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions. *Econ. J.* **125**, 574–620 (2015).
31. Glotter, M. J., Pierrehumbert, R. T., Elliott, J. W., Matteson, N. J. & Moyer, E. J. A simple carbon cycle representation for economic and policy analyses. *Clim. Change* **126**, 319–335 (2014).
32. Arrow, K. et al. Report of the NOAA panel on contingent valuation. *Fed. Regist.* **58**, 4601–4614 (1993).
33. Bateman, I. & Willis, K. (eds) *Valuing Environmental Preferences: Theory and Practice of the Contingent Valuation Method in the US, EU, and Developing Countries* (Oxford Univ. Press, 2001).
34. Champ, P. A., Boyle, K. J., Brown, T. C. & Peterson, L. G. (eds) *A Primer on Nonmarket Valuation* Vol. 3 (Springer, 2003).

35. *Technical Support Document: - Social Cost of Carbon for Regulatory Impact Analysis - Under Executive Order 12866* (Interagency Working Group on Social Cost of Carbon, United States Government, 2010).
36. Beckage, B. et al. Linking models of human behaviour and climate alters projected climate change. *Nat. Clim. Change* **8**, 79–84 (2018).
37. Breiman, L. *Manual On Setting Up, Using, And Understanding Random Forests V3.1* https://www.stat.berkeley.edu/ breiman/Using_random_forests_V3.1.pdf (2002).
38. Lemoine, D. & Traeger, C. P. Economics of tipping the climate dominoes. *Nat. Clim. Change* **6**, 514–519 (2016).
39. Cai, Y. & Lontzek, T. S. The social cost of carbon with economic and climate risks. *J. Polit. Econ.* **127**, 2684–2734 (2019).
40. Traeger, C. P. A 4-stated DICE: quantitatively addressing uncertainty effects in climate change. *Environ. Resour. Econ.* **59**, 1–37 (2014).
41. Crost, B. & Traeger, C. Optimal climate policy: uncertainty versus Monte Carlo. *Econ. Lett.* **120**, 552–558 (2013).
42. Statistical Office of the European Union *Environmental Protection Expenditure Accounts: Handbook* (Eurostat, 2017).
43. Diaz, D. B. Estimating global damages from sea level rise with the Coastal Impact and Adaptation Model (CIAM). *Clim. Change* **137**, 143–156 (2016).
44. De Bruin, K. C., Dellink, R. B. & Tol, R. S. AD-DICE: an implementation of adaptation in the DICE model. *Clim. Change* **95**, 63–81 (2009).
45. Urban, M. C. Accelerating extinction risk from climate change. *Science* **348**, 571–573 (2015).
46. Chaplin-Kramer et al. Global modeling of nature's contributions to people. *Science* **366**, 255–258 (2019).
47. Moore, F. C. et al. Mimi-PAGE, an open-source implementation of the PAGE09 integrated assessment model. *Sci. Data* **5**, 180187 (2018).
48. Anthoff, D., Plevin, R., Kingdon, C. & Rennels, L. *Mimi: An Integrated Assessment Modeling Framework* (2020); https://www.mimiframework.org/
49. Solow, R. M. Is the end of the world at hand? *Challenge* **16**, 39–50 (1973).
50. Stiglitz, J. E. in *Scarcity and Growth Reconsidered* (ed. Smith, V. K.) 36–66 (The Johns Hopkins Univ. Press, 1979).
51. Brandt, N., Schreyer, P. & Zipperer, V. Productivity measurement with natural capital. *Rev. Income Wealth* **63**, S7–S21 (2017).
52. Costanza et al. Changes in the global value of ecosystem services. *Glob. Environ. Change* **26**, 152–158 (2014).
53. Howard, P. H. & Sterner, T. Few and not so far between: a meta-analysis of climate damage estimates. *Environ. Resour. Econ.* **68**, 197–225 (2017).
54. Hsiang et al. Estimating economic damage from climate change in the United States. *Science* **356**, 1362–1369 (2017).
55. Yamaguchi, R. & Managi, S. Backward-and forward-looking shadow prices in inclusive wealth accounting: an example of renewable energy capital. *Ecol. Econ.* **156**, 337–349 (2019).

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Author contributions
B.A.B.-O. and F.C.M. conceived the study, analysed the results and prepared the manuscript. B.A.B.-O. coded the model and performed the simulations.

Competing interests
The authors declare no competing interests.

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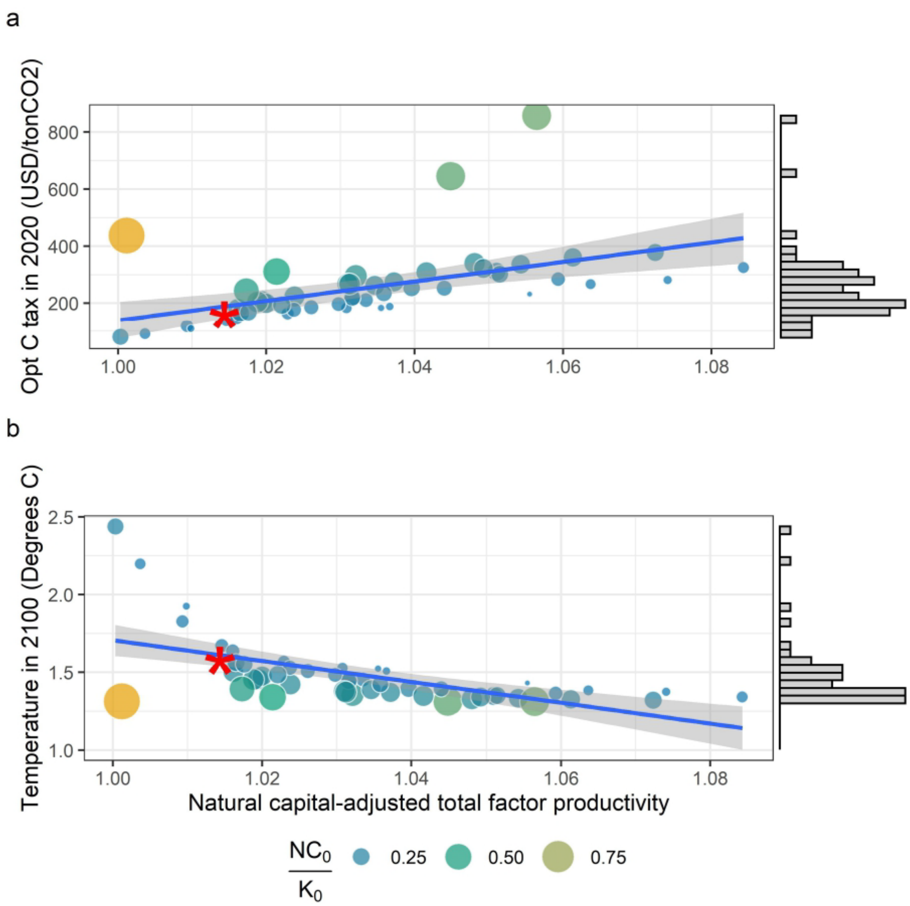
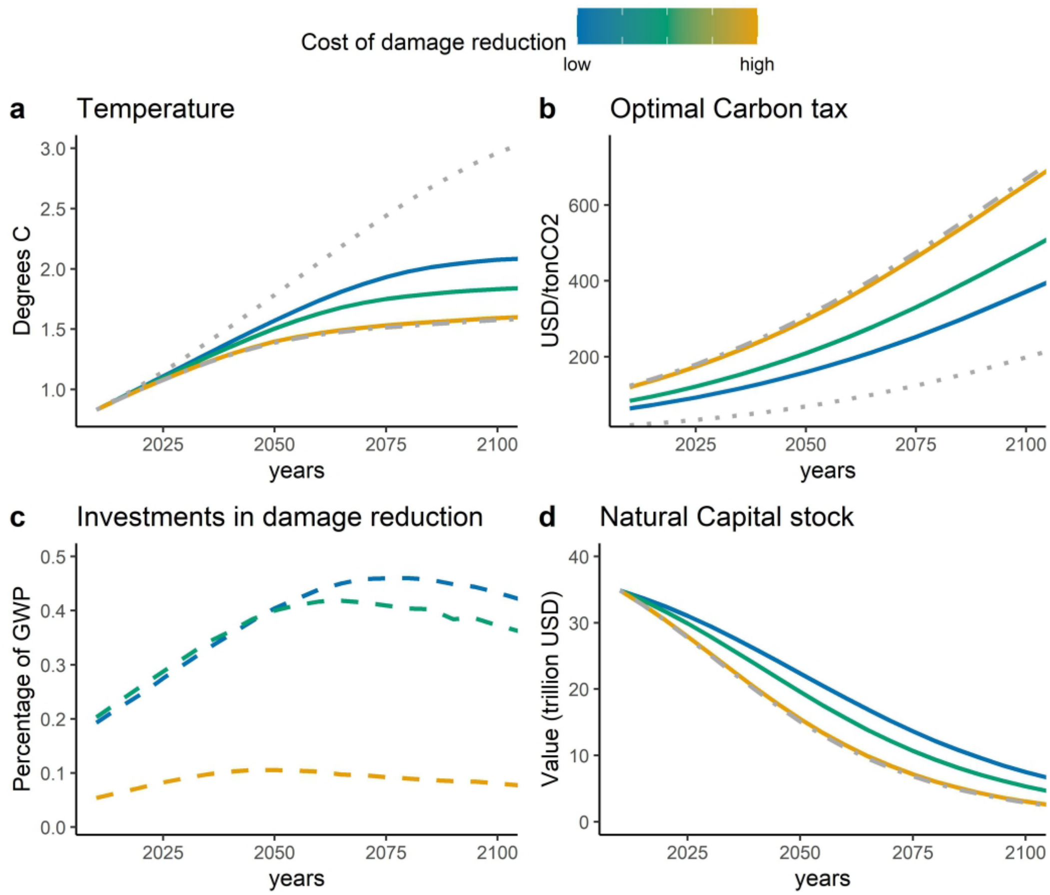
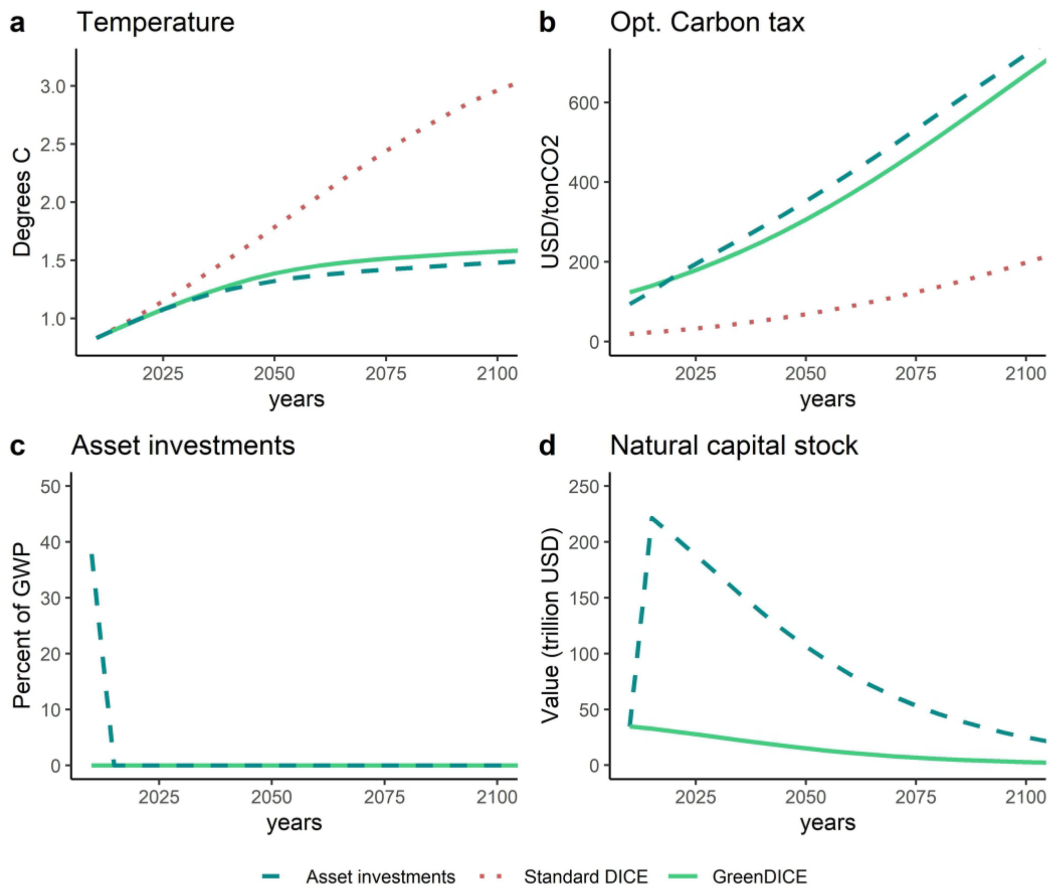


Extended Data Fig. 1 | Effects of different estimates of natural capital. Effects of different estimates of the natural capital-adjusted total factor productivity and natural capital current value relative to current manufactured capital. Red stars give values using the preferred parameter estimates. Size of circles represents the current global estimate of natural capital value with respect to manufactured capital.



Extended Data Fig. 2 | Three levels of adaptation costs. Key policy variables under welfare-maximizing conditions of three levels of adaptation costs. Dotted line is standard DICE, and dashed-dotted line is GreenDICE without investments.



Extended Data Fig. 3 | Investments on natural capital stock. Welfare-maximizing investments on natural capital stock.

Supplementary Table 1. Key parameters and functional forms introduced in GreenDICE. If not specified, the parameter is the same as in DICE 2013.

	Functional form or Parameters	Source	Alternative values used for Monte Carlo analysis or sensitivity analysis
Utility function $U = [[(1 - s)c^{\theta}_{t} + sE_t^{\theta}]^{\theta 2/\theta} + s_2 i_t^{\theta 2}]^{(1-\alpha)/\theta 2}/(1-\alpha)$	Functional form: Nested constant elasticity of substitution	Following Carbone and Smith[4].	
	$\theta 1$ Substitutability parameter between market goods and ecosystem services	0.55, the average value from a subset of empirical studies presented by Drupp[5].	0.74, 0.86, 0.68, 0.69, 0.32, 0.58, -0.16, 0.41, -0.1, 0.73, 0.79, 0.76, 0.80. Estimates compiled by Drupp (2018)[5], a subset of studies that most likely take into account only use-values of nature. Discussed below.
	s1 The relative importance of ecosystem services consumption with respect to consumption of market goods	0.1, from Hoel and Sterner (2007)[6].	0.05, 0.1, 0.15. An arbitrary deviation from 0.1 to test sensitivity.
	$\theta 2$ Substitutability parameter between use and non-use values	0.58, from a subset of studies presented in Drupp (2018)[5].	0.63,0.78,0.62,0.27 Estimates compiled by Drupp (2018)[5], using only the subset of studies that most likely take into account non-use values of nature. Discussed below.
	s2 Relative importance of non-use values flow with respect to consumption	Assumed to be 0.1, following Hoel and Sterner (2007)[6].	0.05, 0.1, 0.15. An arbitrary deviation from 0.1 to test sensitivity.
Econo mic product ion functio	Functional form: extended Cobb-Douglas	Following [2,7]	

	N_0 Initial value of natural capital stock, as a fraction of manufactured capital	$0.258 * K_0$ Income-weighted average of natural capital estimation by income group in 2010, as reported in World Bank's database[8].	Alternative values are given by $\frac{1}{r_{\frac{k}{n}}} K_0$; Where the ratio of initial manufactured capital to natural capital is sampled from the probability density function: $r_{\frac{k}{n}} = N(mean{:}\ 3.87, sd{:}\ 2.11)$ Constructed with the weighted-mean standard deviation of the income groups in the dataset. Discussed above.
	Δa Natural capital-adjusted total factor productivity, which jointly with initial stock of natural capital, determine the elasticity of output with respect to natural capital. Discussed above.	1.0144 Calibrated using the GDP-weighted average of the 17 country-level estimations of the natural capital-adjusted total factor productivity growth from Brandt et al.[3]	Alternative values obtained from the probability distribution function: $\Delta a = N(mean{:}\ 1.0144, sd{:}\ 0.0324)$
Non-use values $i = N^{\gamma 4}$	$\gamma 4$ Non-use values elasticity to natural capital	0.5 Assuming decreasing non-use value returns in natural capital.	0.2, 0.8 Assumption.
Natural capital damage function $N_t = N_{t-1}/(1 + aT^2)$	Functional form: Quadratic function of temperature	Assumption, following economic damage function literature. (Note that Urban[9] finds that extinction risk increases quadratically with temperature).	
	a Coefficient of squared temperature	0.08, calibrated using data and methods from Howard and Sterner (2017)[10]. See calibration below.	Other estimates are obtained by increasing the parameter of total damages by 100% instead of 25%, as proposed by Stern,[11] and followed by Strner and Persson[12] and Drupp and Hansel.[13] A further variation of this parameter is obtained by varying the percentage of damages corresponding to market only (Further discussed below).

Ecosystem services production function $E=aL^{\gamma_1}K^{\gamma_3}N^{\gamma_2}$	Functional form: Cobb-Douglas production function	Assumption, following [2,7]	
	Natural capital and manufactured capital elasticities	Assumed to be the same as the economic production function, but swapped for natural and manufactured capital.	
Reference values	Pure rate of time preference	1.5% DICE2013	0.1%, 1.5% and 3%
	Climate sensitivity	3.2 DICE2013	Drawn from the distribution proposed by Roe and Baker[14], using standard DICE climate sensitivity value as a central estimate.
	Relative risk aversion	1.45 DICE2013	1.08, 1.83 Maximum and minimum values found in the empirical estimations calculated by Evans (2005)[15]
Cost of natural capital damage reduction $I_t = Y_t a d_t^w$	Functional form: similar to the abatement cost functional form in DICE	Assumption following standard DICE	
	w Cost coefficient	5.57 Following estimates from the statistical office of the European Union	2.25, 8.90 Assuming different costs of damage reduction (Discussed below)
Note: all remaining parameters not specified in this table are maintained the same as in DICE2013R, See Nordhaus and Sztorc (2013)[16]			

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Supplementary information

Use and non-use value of nature and the social cost of carbon

In the format provided by the authors and unedited

Supplementary information: Use and Non-Use Value of Nature and the Social Cost of Carbon

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Extended Data Figure 1 shows graphically the interaction between the initial stock of natural capital and its role in economic production. Damages to natural capital have a larger influence on welfare-maximizing climate policy if the natural capital stock is large and has an important role in the production function, represented by a high natural capital-adjusted total factor productivity (see below for additional information). Under high natural capital-adjusted total factor productivity, the 2020 social cost of carbon is higher (Extended Data Figure 1a) and global mean surface temperature in 2100 is substantially lower (Extended Data Figure 1b). In general, these relations are increased by larger natural capital stock.

The more stringent policy variables are given by relatively large ratio of natural to manufactured capital and high natural capital-adjusted total factor productivity, parameters that are associated with low income countries[1]. On the other hand, relatively low optimal carbon tax and relatively high temperatures are produced by parameters associated with rich countries, that could possibly point to a distributional effect that is larger in poorer countries that rely more on natural capital. The red stars represent the income-weighted global totals for the natural capital initial stock and natural capital-adjusted total factor productivity, respectively.

In the following paragraphs we describe the calibration of the natural capital elasticity of production. We include natural capital in the economic production function as proposed by Solow[2]:

$$Y_t = a_t L_t^{\gamma_1} K_t^{\gamma_2} N_t^{\gamma_3} \tag{1}$$

Where a_t is the total factor productivity, L is labor, K is manufactured capital and the γ_i's are the elasticities, which have been widely studied except for γ_3. This parameter is calibrated using the standard DICE initial production Y_0. It is important to consider that the total factor productivity changes when we explicitly account for an extra variable in the production function[3]. This modified TFP is denoted ($\hat{a}_0$). We also use the World Bank has numerical estimates of the ratio of natural capital to produced capital[1], which we will call $r_{n/k}$ so:

$$Y_0 = \hat{a}_0 L_0^{\gamma_1} K_0^{\gamma_2} N_0^{\gamma_3} \tag{2}$$

$$\Rightarrow Y = \hat{a}_0 L_0^{\gamma_1} K_0^{\gamma_2} (r_{n/k} K_0)^{\gamma_3} \tag{3}$$

We will assume that labor elasticity stays as standard DICE (γ_1=0.7) and that the other elasticities are unknown but all three of them add up to 1. This requirement maintains the constant returns to scale (CRS) characteristic of the production function in standard DICE. We note though that there is little evidence, and therefore little empirical justification for this assumption, regarding the returns to scale of natural capital in production, particularly at the highly aggregate level that it appears in this model.

Maintining these assumptions, however:

$$Y_0 = \widehat{a_0} L_0^{0.7} K_0^{\gamma_2} K_0^{\gamma_3} r_{n/k}{}^{\gamma_3} \tag{4}$$

$$Y_0 = \hat{a}_0 L_0^{0.7} K_0^{0.3} r_{n/k}{}^{\gamma_3} \tag{5}$$

$$\left(\frac{1}{r_{n/k}}\right)^{\gamma_3} = \frac{\hat{a}_0 L_0^{0.7} K_0^{0.3}}{Y_0} \tag{6}$$

Given that we want to calibrate with respect to the standard production Y in DICE, we can re-write equation above:

$$\left(\frac{1}{r_{n/k}}\right)^{\gamma_3} = \frac{\hat{a}_0 L^{0.7} K^{0.3}}{a_0 L_0^{0.7} K_0^{0.3}} = \frac{\hat{a}_0}{a_0} \tag{7}$$

A study from OECD has computed the growth rate in the total factor productivity with and without natural capital for many countries[3]. The growth rate X is defined as: $a_{t+1} = X a_t$, therefore the data from the OECD could be used to adjust the total factor productivity in the production function with respect to the standard DICE model. We have that

$$a_t = X a_{t-1} \tag{8}$$

$$\hat{a}_t = \hat{X} a_{t-1} \tag{9}$$

$$\Rightarrow \hat{a}_t = \hat{X} \frac{a_t}{X} \tag{10}$$

Substituting 10 in 7, we have that:

$$\left(\frac{1}{r_{n/k}}\right)^{\gamma_3} = \frac{\hat{X}_0}{X_0} \tag{11}$$

$$\Rightarrow \gamma_3 log\left(\frac{1}{r_{n/k}}\right) = log\left(\frac{\hat{X}_0}{X_0}\right) \tag{12}$$

$$\Rightarrow \gamma_3 = {log\left(\frac{\hat{X}_0}{X_0}\right)} \Big/ {log\left(\frac{1}{r_{n/k}}\right)} \tag{13}$$

$$\Rightarrow \gamma_3 = {log\left(\frac{\hat{X}_0}{X_0}\right)} \Big/ {log\left(\frac{K_0}{N_0}\right)} \tag{14}$$

Uncertainty on γ_3 could be studied by looking into the underlying uncertainty of $\frac{\hat{X}_0}{X_0}$ and $\frac{K_0}{N_0}$, so we will elaborate on each of them.

Brandt and colleagues[3] calculated traditional factor productivity growth (X) and factor productivity growth with natural capital $(\hat{X})$ for 21 countries using data from 1986 to 2008, so we calculated the income-weighted mean and the standard deviation of $\frac{\hat{X}}{X}$ using the yearly 2008 GDP of the countries as weights, such data and calculation could be found in the model repository.

The ratio of produced capital to natural capital for different income groups uses 2010 data from the World Bank DataBank website (databank.worldbank.org). We obtained the income-weighted average and weighted standard deviation based on 2010 GDP of the income groups, Data and calculation can be found in the model repository: https://www.github.com/BerBastien/GreenDICE

We used the mean and standard deviation of the two components of equation 14 to construct the normal distribution functions below that were used to inform uncertainty in the parameter γ_3 used in the sensitivity analysis and Monte Carlo analysis.

$$\Delta a = N(mean: 1.0144, sd: 0.0324)$$

$$\frac{K_0}{N_0} = N(mean: 3.87, sd: 2.11)$$

Supplementary Table 1 shows the values of the introduced parameters along with their references and rationale behind the functional forms of GreenDICE.

The ranges of values given in Supplementary Table 1 were used for 1000 Monte Carlo simulations, with the welfare-maximizing emissions trajectories calculated for each combination of parameters. Results of the simulations were analyzed using a random forest technique, allowing the importance of different parameters in determining optimal policy to be estimated, allowing for arbitrary interactions and non-linearities[17]. Our response variables are the optimal carbon tax in 2020 and the temperature in 2100 and the predictors are the 8 parameters introduced to GreenDICE and varied in the Monte Carlo procedure.

We found the optimal number of subsample variables for the bootstrap using a crossvalidation technique. The number of trees in the forest was 500 as usually set as default[18]. Finally, we measured the importance of the variables by finding the minimum depth at which each variable is found at each tree in the forest. The lower the depth, the earlier the bootstrapping algorithm found that variable in the optimal partioning.In other words, lower minimal depths represent variables that are relatively more important in explaining the variation in either the optimal carbon tax or 2100 temperature. This part of the analysis was done using RandomForest and randomForestExplainer packages in R.

GreenDICE model and code for making the plots can be found in
https://github.com/BerBastien/GreenDICE

We now discuss the implementation of natural capital imvestments. We implemented two separate forms of investment as control variables for welfare maximizing policy. First, we implemented an investment I_t that reduces climate damages on natural capital D_{Nt} by a fraction ad_t, following the functional form of emission reductions in DICE

$$N_{t+1} = N_t - D_{Nt}(1 - ad_t) \tag{15}$$

Where the cost of reducing damages a_t follows the functional form of abatement costs in DICE, which exhibit increasing marginal costs

$$I_t = Y_t \, ad_t^w \tag{16}$$

We calibrated the parameter w based on environmental protection expenditures data from the statistical office of the European Union[19], which calculates annual environmental expenditures to be around 2.1% of the GDP during the period 2006-2014. Therefore, in an optimistic scenario where investing 2.1% of the gross world product reduces 50% of total climate damages on natural capital, we have that

$$0.021\, Y_t = Y_t\, 0.5^w \tag{17}$$

$$w = \frac{\log(0.021)}{\log(0.5)} = 5.57 \tag{18}$$

Under this calibration, reducing 10% of damages would cost only 0.00027% of GWP, but an extra 10% would require 0.013%, which is two orders of magnitude more costly.

We also perform a sensitivity analysis using two alternative percentages: 0.21% of GWP to reduce 50% of damages (called low damage reduction costs) and 21% of GWP to reduce 50% of damages (called high damage reduction costs). Extended Data Figure 2 shows some key policy variables under welfare maximizing conditions for the three levels of damage reduction costs, it shows that lower costs allow more adaptation to global temperature increase and reduce the optimal carbon tax, but higher costs almost fully inhibit investments in damage reduction and rely only in emissions abatement as GreenDICE main specification.

Additionally, we implement a second alternative form of investment by allowing the savings parameter to directly increase natural capital stock. The welfare-maximizing control variables allow for diverting economic output toward purchase of natural capital assets at a price equal to the marginal welfare return with respect to manufactured capital:

$$p_{N,t} = \frac{\partial W_t/\partial N_t}{\partial W_t/\partial K_t} \tag{19}$$

We solved the price path numerically by running iterative optimizations of GreenDICE until obtaining a convergent price and convergent investment path, as shown in Extended Data Figure 3

Under this investment, very large early investments in natural capital increased the initial stock. This much larger stock of natural capital means ecological damages from climate change are correspondingly larger, producing a higher optimal carbon tax and slightly lower temperatures than GreenDICE.

This behavior reveals that the level of natural capital in GreenDICE is lower than what would maximize welfare in the model, since relaxing the constraint on the level of natural capital produces much larger stocks. Parameterizations of the initial capital stock are taken from estimates from the literature on comprehensive wealth accounting, suggesting either that the importance of natural capital in utility is over-estimated in GreenDICE or that current stocks of natural capital are far below optimal levels. Given that many of the benefits provided by ecosystems are public goods, which are notoriously difficult to provide optimally, it would not be surprising if natural capital today were, in fact, lower than welfare-maximizing levels. We note that this model run is illustrative only. In reality, there are likely dynamic constraints that limit the rate at which economic output can be converted into natural capital. Given the difficulty of representing or parameterizing these relationships at the aggregate and highly abstract level that would be required for GreenDICE, we do not attempt to model them here but simply note that findings should be interpreted cautiously.

We now discuss the substituability parameters. We calibrated the parameters θ_1 (substitutability between welfare by market goods and ecosystem services) and θ_2 (substitutability between use and non-use values) using the empirical estimates collected in Table 1 of the research done by Drupp (2018).[5] We divided such estimates based on whether they were refering to use or non-use values, as shown below.

Estimates used to inform θ_1 (substitutability between welfare by market goods and ecosystem services):

Supplementary Table 2. Studies informing the substitutability parameter θ_1		
Substitutability parameter	**Source**	**Description**
0.74	Barbier et al. (2015)	Water quality improvement
0.86	Barton (2002)	Water quality improvement
0.68	Carlsson and Johansson-Stenman	Air quality improvement
0.69	Chiabai et al. (2011)	Agreggate forest services
0.32	Hokby and Soderqvist (2003)	Aggregate environemntal services
0.58	Liu and Stern (2008)	Aggregate marine services
-0.16	Martini and Tiezzi (2014)	Air quality improvement
0.41	Ready et al. (2002)	Water quality improvement
<0	Schlapfer and Hanley (2003)	Landscape ammenities
0.73	Wand and Whittington (2000)	Air quality improvement
0.79	Wang et al. (2013)	Water quality improvement
0.76	Whitehead et al. (2000)	Recreation improvements
0.80	Yu and Abler (2010)	Air quality improvement

Estimates used to inform θ_2 (substitutability between use and non-use values)

Supplementary Table 3. Studies informing the substitutability parameter θ_2		
Substitutability parameter	**Source**	**Description**
0.63	Broberg (2010)	Existence of predator species
0.78	Hammit et al. (2001)	Wetland preservation
0.62	Jacobsen and Hanley (2009)	Aggregate biodiversity
0.27	Lindhjem and Tuan (2012)	Aggregate biodiversity

Full refreences to such studies could be found in Drupp (2018) [5]

We now discuss the calibration of the damage function. We calibrated the damage parameters to fit the coefficients of DICE2013[16] following the approach used in Drupp and Hansel (2020)[13], but relying on data and code from Howard and Sterner (2017)[10] and results from Hsiang et al (2017)[20] to exclude mortality costs from the non-market ecosystem damages.

Following Drupp and Hansel, we calibrate the damage functions such that contemporaneous welfare changes at the 2.5° calibration point for DICE 2013 are the same using the aggregated and disaggregated utility functions given the same values of ecosystem services (E), consumption of market goods (C) and non-use values (i):

$$W\left(E_0, \left(1 - D^T\right)C_0, i_0\right) = W(\left(1 - D^E\right)E_0, \left(1 - D^k\right)C_0, \left(1 - D^i\right)i_0) \tag{20}$$

Where D^T are the aggregated damages given by the original DICE2013 coefficient, D^E, D^K, and D^i are the damages that we want to calibrate. Expanding each component of the right-hand side of the equation (20) by using the production functions depicted in the methods and the ratio of manufactured capital to natural capital, we have that:

$$(1-D^E)E_0 = (1-D^E)a_0 L_0^{\gamma_1} K_0^{\gamma_3} N_0^{\gamma_2} \quad (21)$$

$$= a_0 L_0^{\gamma_1} K_0^{\gamma_3} \left(\frac{N_0}{1+a_n T^2}\right)^{\gamma_2} \quad (22)$$

$$= a_0 L_0^{\gamma_1} K_0^{\gamma_3+\gamma_2} \left(\frac{r_{n/k}}{1+a_n T^2}\right)^{\gamma_2} \quad (23)$$

$$= C_0 \left(\frac{r_{n/k}}{1+a_n T^2}\right)^{\gamma_2} \quad (24)$$

Similarly for the other components,

$$(1-D^i)i_0 = K_0^{\gamma_4} \left(\frac{r_{n/k}}{1+a_n T^2}\right)^{\gamma_4} \quad (25)$$

$$(1-D^k)C_0 = \left(\frac{1}{1+a_k T^2}\right) C_0 \left(\frac{r_{n/k}}{1+a_n T^2}\right)^{\gamma_3} \quad (26)$$

Where a_k is the damage coefficient that corresponds only to damages on market goods. By plugging equation 24, 25 and 26 in equation 20, we obtain the unknown coefficient a_n (the damage coefficient on natural capital). To do this, we first need to disambiguate a_k (the damages on all things that are not natural capital) from the total damages included in the standard DICE 2013 damage function.

We used a meta-analytic approach to estimate the coefficient a_k using the studies referenced in Nordhaus and Sztorc[16] as informing the DICE2013 damage function. Following the approach in Howard and Sterner (2017), we model the change in welfare reported in these studies (summarized in Howard and Sterner 2017) as a quadratic function of the change in temperature (t2) and two dummy variables: studies that only included market impacts and studies measuring different measure of welfare (consumer surplus vs willingness to pay). The results are shown in Supplmentary Table 4

Supplementary Table 4. Results of regression model

	Dependent variable: damage
t2	0.222***
	(0.053)
mkt_t2	-0.151
	(0.147)
method_control	-0.069
	(0.148)
Observations	13
R2	0.656
Adjusted R2	0.553
Residual Std. Error	1.158 (df = 10)
F Statistic	6.362** (df = 3; 10)
Note:	*p<0.1; **p<0.05; ***p<0.01

Therefore, the market-only impacts (0.222 – 0.151) correspond roughly to 32% of the total impacts (0.222), which lies within the 30-50% range estimate of an expert opinion survey done by Howard and Sylvan[21]. However, it is important to note that health impacts (i.e. mortality and morbidity as a result of climate change) is a component of non-market damages unrelated to changes in natural capital. We therefore adjust the estimated coefficient using the results of Hsiang et al (2017)[20] who found that at 2.5°C above pre-industrial – which is the same calibration point used by most studies that inform DICE2013 damage function - roughly 20% of total impacts are attributable to mortality in the United States. Extrapolating from this country-level study to inform the global damage function, we have that 48% of the total damages account for natural capital damages, recognizing that this extrapolation is not ideal.

Therefore, $a_k = 0.52 * a_d$, where $a_d = 0.00267$ is the original DICE2013R coefficient Once a_k is obtained, we use the equation 20 to find the coefficient a_n numerically. The preferred estimate using the central values above, yields $a_n = 0.08$

For the Monte Carlo analysis and the sensitivity analysis, we sampled from probability distribution functions of the different parameters used to get a_k and a_n, which are:

Supplementary Table 5. Uncertainty of the parameteres used to calculate the damage funciton.		
Parameter	Preferred value	Alternative values
a_d: total damages	The preferred value of $a_d = 0.00267$ as in DICE2013R, which already accounts for the 25% increment due to omitted variables.	An alternative value would be to increase the damage by 100% instead of 25%, as proposed by Stern[11] and followed by Sterner and Persson[12] and Drupp and Hansel[13]
Percentage of market-only impacts	Given the regression results above, we have that market-only impacts account for 32% of the total damages.	We use the standard error of that parameter to construct a probability density function that we can use for sampling.

Alternative calibrations, beyond the scope of this paper, could be informed by previous studies that focus on specific damages to consumption, for example the work by Brooks and Newbold on damage to biodiversity non-use values[22].

Supplementary Information 7: Utility function in different versions of GreenDICE

We show below the utility finction of the different specifications. Recalling the GreenDICE utility function:

$$u(f) = \frac{f^{1-\alpha}}{(1-\alpha)} = \frac{\left[\tilde{c}_t^{\theta_2} + s_2 i_t^{\theta_2}\right]^{\frac{1-\alpha}{\theta_2}}}{(1-\alpha)} = \frac{\left[\left((1-s_1)c_t^{\theta_1} + s_1 e_t^{\theta_1}\right)^{\frac{\theta_2}{\theta_1}} + s_2 i_t^{\theta_2}\right]^{\frac{1-\alpha}{\theta_2}}}{(1-\alpha)} \tag{27}$$

We have that all the versions of GreenDICE's utility function are given by modifying the parameters s_1, s_2, θ_1, and θ_2 to include or exclude different components of the utility function.

Full GreenDICE utility function:

$$u_t = \frac{\left[\left((1-s_1)c_t^{\theta_1} + s_1 e_t^{\theta_1}\right)^{\frac{\theta_2}{\theta_1}} + s_2 i_t^{\theta_2}\right]^{\frac{1-\alpha}{\theta_2}}}{(1-\alpha)} \tag{28}$$

All-use values utility function:

$$u_t = \frac{\left[(1-s_1)c_t^{\theta_1} + s_1 e_t^{\theta_1}\right]^{\frac{1-\alpha}{\theta_1}}}{(1-\alpha)} \tag{29}$$

Market-only utility function:

$$u_t = \frac{c_t^{1-\alpha}}{(1-\alpha)} \tag{30}$$

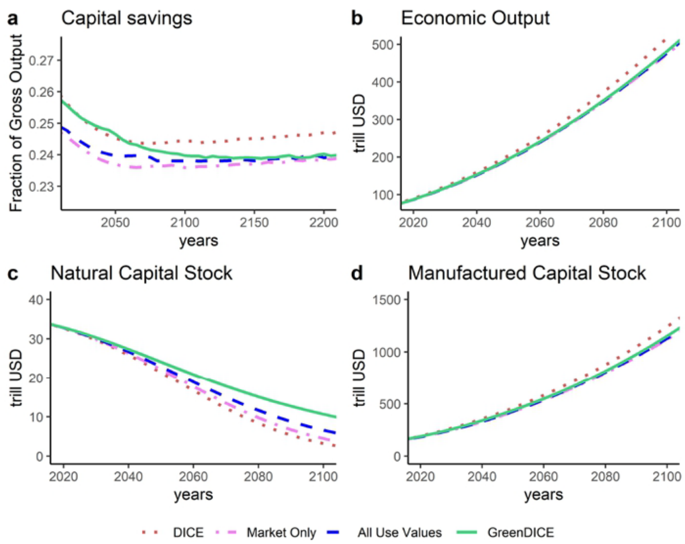
We discuss below the key differences of GreenDICE and other well-known models. The main difference between GreenDICE and other well-known models developed by Hoel and Sterner and further studied by Drupp and Hansel (henceforth called HSDH model) is that in GreenDICE climate damages the stock that produces ecosystem services (i.e. natural capital), which causes persistent losses in welfare. In contrast, HSDH model introduced climate impacts directly in the level of the ecosystem services. A second difference is that, while HSDH calibrated the damage function assuming an increase of 100% of the standard DICE coefficient (following Stern[11]), we calibrated the damage function assuming an increase of only 48%, which we vary as part of the sensitivity analyses (See supplementary information 6).

Another key difference between the models that also reduces the differences between both model results is the choice of θ_1. While Hoel and Sterner assumed $\theta_1 = -1$ (i.e. strict complements) and Drupp and Hansel use $\theta_1 = -0.11$ in their preferred calibration, we used estimates from Drupp (2018)[5] detailed in Supplementary Informatin 5, to give $\theta_1 = 0.54$, implying imperfect substitutibility of both types of goods (market and ecosystem services).

Finally, it is important to note that GreenDICE is based on DICE-2013Rs, not the more recent DICE-2016R2, which includes new projections of population, economic growth, and carbon intensity and begins in 2015 instead of 2010. These changes could change the specific numbers in the results, such as the projected emissions, which would start closer to 2020, but are very unlikely to alter any conclusions. This is particularly true since many of the updates to specific parameters in DICE-2016R2 are already varied in our sensitivity analysis, for example, the damage function parameter and the climate sensitivity.

Below we show the behavior of savings and capital stocks. Other interesting variables that may be helpful further to understand the behavior of the different versions of GreenDICE are the savings rate and the stocks of manufactured and natural capital as shown in Supplementary Figure 1. We can see that while there is no significant change in the capital savings rate, the economic output, and the associated manufactured capital stock, the natural capital stock shows a different path for the different versions of GreenDICE. Higher stocks of natural capital are related to lower temperatures over the

21st century under optimal mitigation rates. Further information can be found in the GitHub repository of this model.

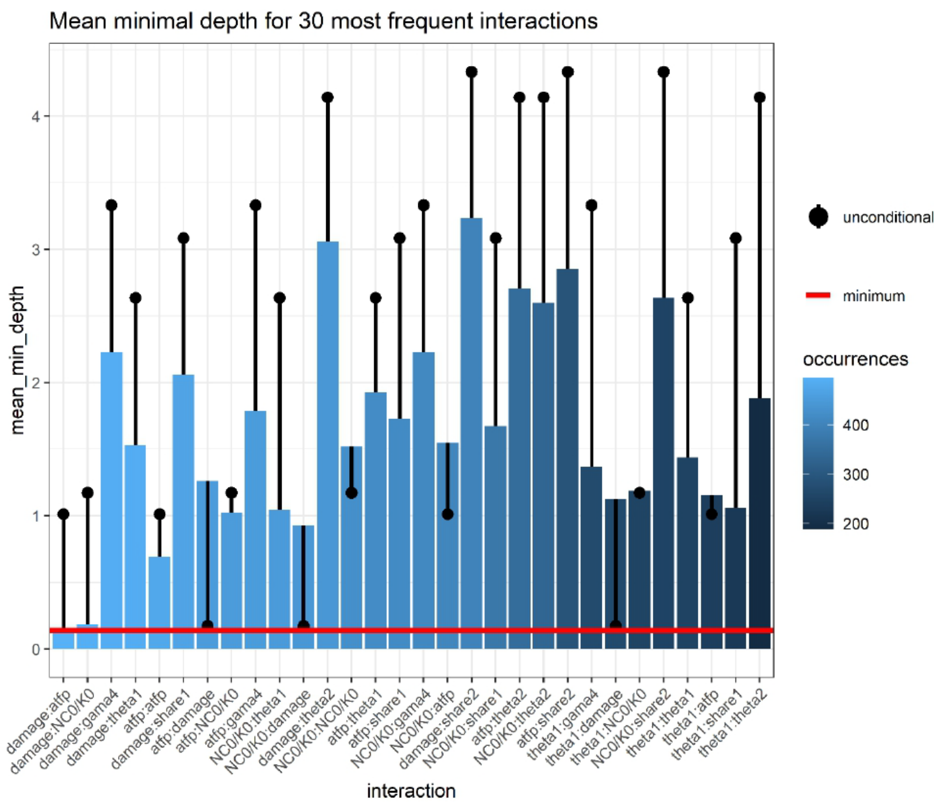


Supplementary Figure 1. Savings rate and stocks.

We now discuss important interactions between parameters. Further investigation of the relationships driving variation in the outcomes of interest is shown in Figure S5. This highlights critical interactions revealed in the random forest by identifying an important parameter (with low minimal depth) and then identifying which parameter tends to appear immediately after it (conditional minimal depth), which mean that those two parameters are important drivers of the variables of interest (SCC in 2020 or temperature in 2100)[23]. Figure S4 shows the conditional minimal depth of the 30 most frequent parameter interactions in the random forest generated to analyze the Monte Carlo analysis.

Figure S4 shows two significant interactions, one between the natural capital-adjusted total factor productivity and the damage parameter and another between the damage parameter and the parameter and the initial stock of natural capital (NC0/K0). This interaction is important not only because of the low mean minimal value, but also because it occurs many times in the random forest as shown by the color gradient.

Low value of natural-capital adjusted total factor productivity and low level of damages to natural capital yield a low SCC, while a combination of high levels in such parameters yield a high SCC in 2020. Together these findings suggest, perhaps unsurprisingly, that the importance of natural capital in providing human welfare and the extent to which climate change will damage natural capital are jointly important determinants of optimal climate policy in GreenDICE.



Supplementary Figure 2. Important parameter interactions ordered by most frequent. Height of the bars indicate the importance of the interaction as given by the mean minimum depth.

Finally, we show the components of the social welfare funciton in different versions of GreenDICE in Supplementary Table 6.

Supplementary Table 6. Components of the social welfare function in different versions of GreenDICE.

Component in the social welfare function	Type of value and description	Versions that include the component	Production process
Existence value	Non-use value. Existence value of species and ecosystems	Full GreenDICE	$i=N^{\gamma 4}$
Ecosystem services	Use value. Includes all non-market ecosystem services, with the excpeption of carbon sequestration (see discussion in main text). Example of included ES in this category: recreation, cultural uses..	All use-values, full GreenDICE	$E=aL^{\gamma 1}K^{\gamma 3}N^{\gamma 2}$
Market goods and services	Use value. All goods and services that have a market price, for example, provisioning ecosystem services. Mortality impacts are non-market goods but are maintained in this comprehensive good through calibration of the damage function (See Supplementary Information 6).	Market-only; All-use values, full GreenDICE	$Y=aL^{\gamma 1}K^{\gamma 2}N^{\gamma 3}$

Supplementary Information References

1. Lange, G.-M., Wodon, Q. & Carey, K. *The changing wealth of nations 2018: Building a sustainable future*. (The World Bank, 2018).
2. Solow, R. M. Is the End of the World at Hand? *Challenge* **16**, 39–50 (1973).
3. Brandt, N., Schreyer, P. & Zipperer, V. Productivity measurement with natural capital. *Review of Income and Wealth* **63**, S7–S21 (2017).
4. Carbone, J. C. & Smith, V. K. Valuing nature in a general equilibrium. *Journal of Environmental Economics and Management* **66**, 72–89 (2013).
5. Drupp, M. A. Limits to substitution between ecosystem services and manufactured goods and implications for social discounting. *Environmental and Resource Economics* **69**, 135–158 (2018).
6. Hoel, M. & Sterner, T. Discounting and relative prices. *Climatic Change* **84**, 265–280 (2007).

7. Cobb, C. W. & Douglas, P. H. A Theory of Production. *The American Economic Review* **18**, 139–165 (1928).
8. World Bank. Wealth Accounts | DataBank. https://databank.worldbank.org.
9. Urban, M. C. Accelerating extinction risk from climate change. *Science* **348**, 571–573 (2015).
10. Howard, P. H. & Sterner, T. Few and not so far between: a meta-analysis of climate damage estimates. *Environmental and Resource Economics* **68**, 197–225 (2017).
11. Stern, N. Stern review report on the economics of climate change. (2006).
12. Sterner, T. & Persson, U. M. An even sterner review: Introducing relative prices into the discounting debate. *Review of Environmental Economics and Policy* **2**, 61–76 (2008).
13. Drupp, M. A. & Hänsel, M. C. Relative prices and climate policy: How the scarcity of non-market goods drives policy evaluation. *forthcoming at the American Economics Journal: Economics Policy* (2020).
14. Roe, G. H. & Baker, M. B. Why is climate sensitivity so unpredictable? *Science* **318**, 629–632 (2007).
15. Evans, D. J. The elasticity of marginal utility of consumption: estimates for 20 OECD countries. *Fiscal studies* **26**, 197–224 (2005).
16. Nordhaus, W. & Sztorc, P. DICE 2013R: Introduction and user's manual. *retrieved November* (2013).
17. Breiman, L. Bagging predictors. *Machine learning* **24**, 123–140 (1996).
18. Breiman, L. *Manual On Setting Up, Using, And Understanding Random Forests V3.1*. https://www.stat.berkeley.edu/ breiman/Using_random_forests_V3.1.pdf (2002).
19. Statistical Office of the European Communities. *Environmental protection expenditure accounts: handbook.* (Eurostat, 2017).
20. Hsiang, S. *et al.* Estimating economic damage from climate change in the United States. *Science* **356**, 1362–1369 (2017).

21. Howard, P. H. & Sylvan, D. The Economic Climate: Establishing Expert Consensus on the Economics of Climate Change. *Institute for Policy Integrity* 438–441 (2015).

22. Brooks, W. R. & Newbold, S. C. An updated biodiversity nonuse value function for use in climate change integrated assessment models. *Ecological Economics* **105**, 342–349 (2014).

23. Paluszynska, A., Przemyslaw, B. & Jiang, Y. *R Package 'randomForestExplainer'*. (2019).

Chapter 2

Forests range shifts under climate change: impacts on macro-economic growth and human wellbeing

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Forests range shifts under climate change: impacts on macro-economic growth and human wellbeing

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ABSTRACT

Ecosystems contribute to human well-being through market and non-market benefits. As climate change influences ecosystems distribution throughout the world, these benefits will change. However, the degree and even the direction of the impact will depend on how ecosystems will shift and to what extent countries rely on them for their market and out-of-market activities. In this work, we simulate country-level ecosystem services and economic growth using reduced-form macro-economic models with natural capital as a productive asset. We estimate climate change damages to natural capital through a random forest algorithm that combines outputs from a dynamic terrestrial ecosystem model, an ecosystem services valuation database, and the World Bank inclusive wealth accounts. Our results show that the mean global flow of ecosystem services are reduced by 32% in 2100 under the SSP2-4.5 (~2.6°C), and the mean global GDP decreases 1.5% in 2100, having larger effects on African countries (-5%) and dampening as country-level wealth increases. Limiting temperature below 2°C could cut damages on GDP and ecosystem services at least by half and reduce economic inequality among countries.

As ecosystems are disrupted and shift due to climate change[1–3], countries with higher dependency on natural capital have more at stake. Current approaches that inform climate policy by analyzing the social welfare consequences of climate change have not explicitly included this dependency in its two major forms. First, countries from the global south still heavily rely on the raw materials obtained from ecosystems to grow their economies. Second, societies hold non-market values in relation to their natural systems that give rise to a diverse flow of benefits. Failing to account for these nature contributions to people (NCP) underestimates the potential climate change damages that highly natural capital-dependent countries will bear in the future.

At the core of society lie different types of valuable assets that produce a flow of market and non-market benefits to people. Sustainability literature has focused on measuring increasingly comprehensive estimates of wealth and doing backward-looking assessments of whether inclusive wealth has declined over time or not, complying with the primary requisite for sustainability[4–8]. However, less has been done to analyze climate change impacts on the future trajectories of comprehensive wealth and its implications for society.

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This study analyzes such impacts by estimating the effect of changing ecosystems under climate change scenarios on future economic growth and the flow of ecosystem services provided by forests.

Cost-benefit integrated assessment models (IAMs) couple the climate and economic system to calculate policy-relevant quantities like the social cost of carbon (SCC), which measures the welfare effects of a ton of carbon dioxide emitted to the atmosphere in a given year. In principle, these models should have a fully comprehensive accounting of the damages. However, in the three most used IAMs today (DICE[9], PAGE[10], and FUND[11] models), climate impacts on ecosystems are usually absent, or when present, they fail to capture recent estimates of ecosystem services valuation and ecological dynamics of ecosystems[12].

This work estimates climate impacts on country-level economies and ecosystem services by building on economic growth and welfare models consistent with the inclusive wealth literature. Our economic growth model builds on the standard two-factor neoclassical growth model[13] used in IAMs in which an exogenously growing human capital and an endogenous manufactured capital stock determine production and growth. As shown in Figure 1 (left), we expand the production function to include natural capital as a third factor required for economic production and only partially substitutable by the more standard manufactured and human capital. As another component of human wellbeing, ecosystem services arise from natural capital independently of the production function of market goods.

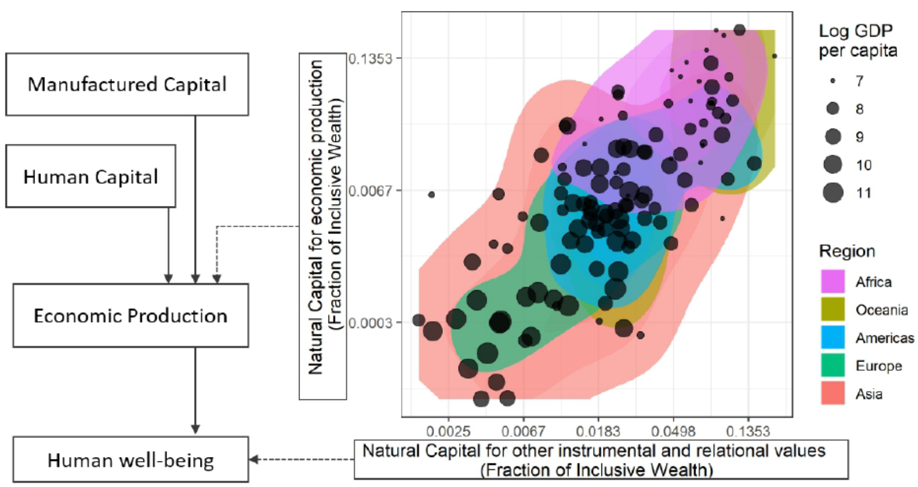


Figure 1. Natural capital is an input for market and non-market components of human well-being. Left: Natural capital for economic production interacts with manufactured and human capital to produce economic output, while natural capital for other instrumental and relational values generates ecosystem services. Right: country-level estimates of market and non-market natural capital as a fraction of total inclusive wealth using World Bank data.

Inclusive wealth accounting literature has disaggregated natural capital based on the nature of the benefits they generate and the type of natural systems that they rely on[4]. We focus on natural capital associated with the market and nonmarket forests' benefits to people using the estimates of the World Bank inclusive wealth accounts. Within-market natural capital associated with forests (mN) is given by the present value of the flow of timber and other wood products found in the market. On the other hand, nonmarket natural capital associated with forests and protected areas (nN) is given by the present value of the flow of ecosystem services (water quality and quantity, recreation, and non-wood products) provided by forests and the option value associated with protected areas.

Figure 1 (right) shows that a larger fraction of low and middle-income countries' wealth comprises those two types of natural capital. Therefore, for a fixed loss of forest cover, those countries are the ones that will be more affected (See Supplementary Figure 1). However, two main factors modulate these losses. First, the ecological response of ecosystems to climate change may vary, ranging from functionality decline and biodiversity loss to expansion in areas that provide new conditions matching the ecosystem's climate niche. Second, each country's cultural and economic histories imprint an idiosyncratic value on their different ecosystems. We use outputs from a terrestrial vegetation model and a database of ecosystem services studies to estimate these relationships (see Methods).

Ecosystems respond to carbon dioxide concentrations, temperature, and water availability changes. Warmer and drier conditions have increased fires, droughts, and insect activity, while warmer and wetter conditions have strengthened wind disturbance and pathogen activity[14]. These impacts affect forests' productivity and functionality, which, combined with macro-ecosystem dynamics, provide the whole picture of climate impacts on forests[15]. We retrieve the ecosystem's range shift projections under future climate change scenarios using the LPJ-Guess, a process-based vegetation-terrestrial ecosystem model designed to predict the behavior of Earth's ecosystems[16]. Figure 3 shows the present and future distribution of 11 types of plant functional types (PFTs) forced by climate drivers only (carbon dioxide, temperature, and rainfall) under the SSP2-4.5 scenario[17]. Overall, we see that tropical vegetation expands at the cost of temperate ecosystems, and most types of boreal vegetation show a decline (Figure 3 left). Further, most of the globe loses natural vegetation cover by the end of the century except for northern latitudes and a few dry places in Australia and Sharan Africa (Figure 3, right).

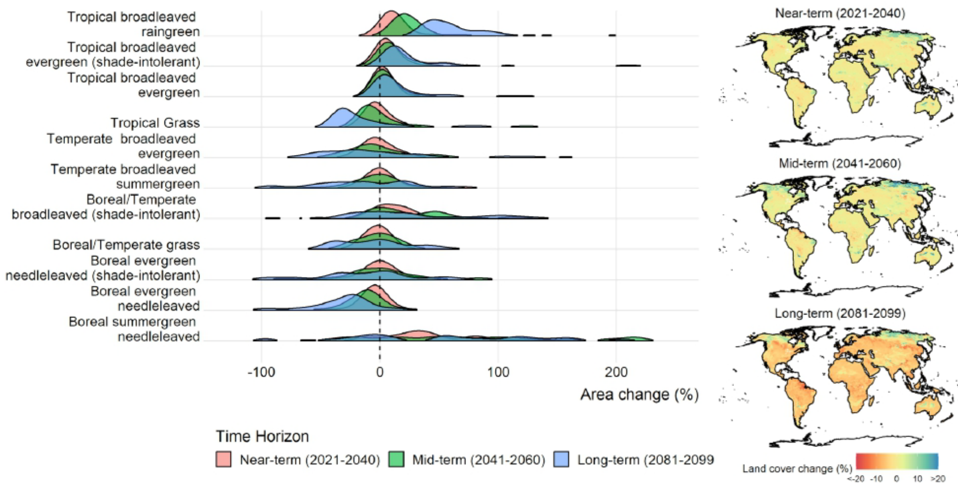


Figure 3. Ecosystem changes at different time horizons under RCP6.0. Left panel: area changes on plant functional types. Right panel: percentage of grid cell covered by natural vegetation. Model output from LPJ-Guess, a terrestrial ecosystem model part of the simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b)[17]

Using the Value of Ecosystem Goods and Services (VEGS) database, we map the current natural capital values calculated by the World Bank to the types of ecosystems currently present in each country according to the dynamic vegetation-terrestrial model. Non-market natural capital at time t is given by

$$nN_{t,c} = \Sigma_{PFT} \frac{a_{t,c,PFT}\, es_{t,c,PFT}}{r} \qquad \text{eq. 1}$$

Where $es_{t,c,PFT}$ is the value of the flow of benefits or ecosystem services provided by a hectare of the ecosystem associated with each PFT in country c at time t, and $a_{t,c,PFT}$ is the area coverage of such PFT in country c at time t. Since we have the present estimates for both the non-market natural capital value (nN) and the coverage area of each PFT, we can calculate the relative contribution of each PFT to the total natural capital value using economic studies of ecosystem services values. To do that, we combine the ecosystem services values recorded in the VEGS database with the present-day PFTs cover area for the geographic extent of the area studied. We apply a random forest algorithm to estimate the relative contribution of each PFT to the total value of a subsample of observations from the VEGS database that maps to the two types of natural capital analyzed in this study (provisioning and non-provisioning). Using that, we obtain country-level estimates of ecosystem services value per hectare for each PFT (Figure 4).

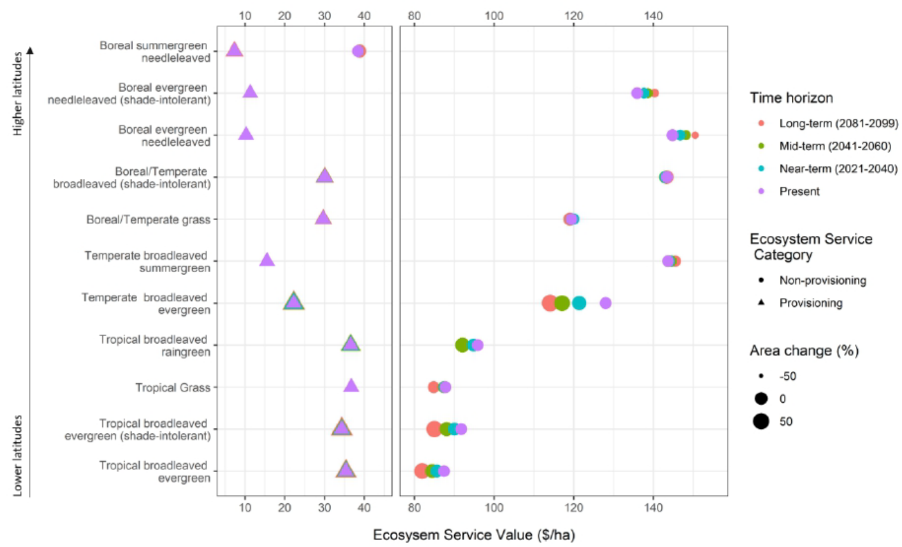


Figure 4. Ecosystem services value ($/ha) for each type of PFT and for the two types of natural capital (market/provisioning and non-market/non-provisioning).

Using the PFT-level values per hectare and the LPJ-Guess terrestrial dynamic model output under SSP2-4.5, we project climate effects on the two types of natural capital (Supplementary Figure 2). We use those projections to fit a quadratic equation to the level of natural capital damage as a function of global mean surface temperature change.

Following the reduced-form economic and welfare model depicted in Figure 1 (see Methods), we project country-level market and non-market benefits into the future under damaged natural capital. Figure 5 shows the changes in GDP and ecosystem services trajectories under the SSP2-4.5 scenario with respect to a baseline scenario where natural capital is not damaged by climate change.

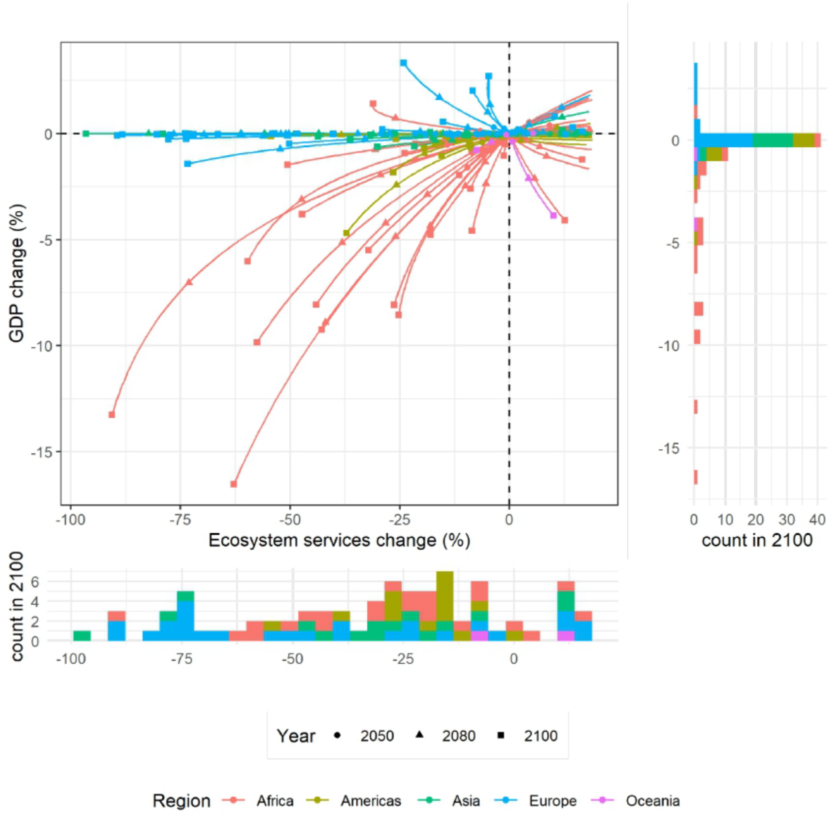


Figure 5. Market and non-market impacts under SSP2-4.5 scenario. Trajectories of the change in GDP and Ecosystem services are shown for 146 countries with respect to simulations without climate change impacts.

Two contrasting results arise. First, regardless of their geographic region, many countries will lose a large proportion of their ecosystem services with respect to the baseline. The global average change of ecosystem services by 2100 is -32.1%. Only a few will get benefits from ecosystem shifts under climate change conditions. These changes seem not to be related to the country's GDP or geographic region (See supplementary Figure 3). While the literature on the wealth influence on non-market values of nature indicates that demand for conservation rises with GDP[18], this relationship seems not to hold for the changes in ecosystem services due to climate change impacts.

On the other hand, the changes in GDP are smaller in magnitude but more differentiated by region. The average change in GDP by 2100 is -1.5%, but the region with the lowest mean value is Africa (-5%), while Europe sees an average GDP increase of 0.3% by 2100 with respect to the baseline. These results show how the climate change effects on ecosystems could further increase inequality operating through the provisioning services of ecosystems, which are especially important in low and lower-middle income countries[19].

Reducing emissions to comply with the recently pledged nationally determined contributions of greenhouse gases and limiting warming below 2°C[20] would cut the impacts of GDP by a third (global mean change by 2100: -0.5%) and the impacts on ecosystem services by half (global mean change by 2100: -15%) compared to the SSP2-4.5 that puts the planet at 2.6°C of warming by 2100 with respect to preindustrial levels.

While other drivers such as direct ecosystem degradation or depletion are currently the most influential in ecosystemic functioning and biodiversity conservation, climate change puts ecosystems increasingly at risk.

METHODS

Growth simulations

We simulate economic growth based on a version of the neoclassical Solow-Swan model of economic growth[13] extended to account for market natural capital. We use the World Bank data inclusive wealth estimates[21] of 2018 to project each country's future economic growth. We simulate growth pathways from 2018 to 2100 fixing country-level human capital (H) and total factor productivity (TFP) to 2018 levels, allowing for manufactured capital (K) accumulation through savings (s=0.03) and depreciation (d=0.1), and market natural capital (eN) damaged by future temperature trajectories (see below). We use the following three-factor Cobb-Douglas production function:

$$GDP_{t,c} = TFP_c * H_c^{\gamma_1} * K_{t,c}^{\gamma_{2,c}} * eN_{t,c}^{\gamma_{3,c}}, \qquad \text{eq. 2}$$

The production elasticity to human capital γ_1 is estimated by the following GDP-weighted panel regression model

$$log(GDP_{t,c}) = \hat{\gamma}_1 log(H_{t,c}) + \hat{\gamma}_2 log(K_{t,c}) + \hat{\gamma}_3 log(eN_{t,c}) + \theta_t + \theta_c + \epsilon_{t,r} \qquad \text{eq. 3}$$

where θ_t and θ_c are year and country fixed effects and standard errors are clustered by geographic region. $\hat{\gamma}_1 = 0.54$ with a p-value < 0.001 (See supplementary table 1). Following work from Brandt et al.[22], we use the country-level share of timber rents on GDP as the production elasticity to market natural capital $\gamma_{3,c}$. The production elasticity to manufactured capital is obtained assuming constant returns to scale, i.e. $\gamma_{2,c} = 1 - \gamma_1 - \gamma_{3,c}$, Supplementary Table 2 shows the country-level values used in equation 2.

Ecosystem services and natural capital

Natural capital is part of society's productive base, producing market and non-market benefits flows. Following Dasgupta[23] the total natural capital stock at time t can be written as the sum of individual natural assets (soils, forests, wetlands etc) multiplied by their shadow price

$$N_t = \sum_i p_i(t) n_i(t), \qquad \text{eq. 4}$$

The shadow price, $p_i(t)$ gives the present value of the stream of benefits derived from an additional unit of the natural asset n_i. Therefore, equation 4 can be written as

$$N_t = \sum_i \sum_t^T \frac{ES_i(t)}{(1+r)^t} \qquad \text{eq. 5}$$

Where $ES_i(t)$ is the total yearly flow of ecosystem services from the natural asset i at time t. For ecosystem goods other than crops, fish, or timber (where market prices are readily observable), measuring the value of services can be particularly challenging since it requires the application of non-market valuation approaches. Projecting estimates of this value in the future adds further complexity as one should make assumptions on how the natural assets will be managed and impacted in the future and whether the preferences of the population will change, either exogenously or as a function of the asset stock itself[24].

As the role of natural capital becomes increasingly evident, both the World Bank and the UN Environment Program (UNEP), have been developing approaches to incorporate natural capital accounting into national accounts data[4,25–27]. We use the World Bank Changing Wealth of Nations 2021 report[4] estimates of natural capital, excluding natural capital values related to non-renewable resources (e.g. minerals), non-terrestrial ecosystems (e.g. fisheries), and cropland whose relation with climate change has been extensively reviewed in the past. In turn, we focus on natural capital provided by natural terrestrial ecosystems. We call market natural capital (eN) the estimate of natural capital provided by timber products of forests. Non-market natural capital (nN) is given by non-timber benefits from forests (recreation, watershed protection, and other nonwood forest products) and values of protected areas.

Equation 5 can be disaggregated by types of ecosystems and rewritten into equation 1 following the World Bank assumptions of no forest area change in the future and constant per hectare value of forests' annual services over 100 years. The ecosystem services annual value per hectare of each PFT are calculated using the known values of equation 1: non-market natural capital value in 2018 (eN), and the coverage area of each PFT within each country calculated from the LPJ-Guess model output average from 2016 to 2020. We can rewrite equation 1 in terms of the fraction x_{PFT} that each PFT contributes to the overall value of ecosystem services annual flow within each country:

$$nN_{t,c} = \Sigma_{PFT} \frac{a_{t,c,PFT}\, x_{PFT}\, ES_{t,c}}{r} \qquad \text{eq. 6}$$

To get x_{PFT} we use the VEGS database. This database records 882 ecosystem services annual values per hectare reported in 276 ecosystem services studies that use original valuation methods (i.e. excluding metanalysis and value transfer). We retrieved the geographic boundaries of the reported locations of the studies. We used them to extract the PFT-covered area values for each observation according to the LPJ-Guess model output from 2016 to 2020. For each country, we take a subsample of the database that contains observations with non-zero PFT-cover area values of the most abundant ecosystem of such country. With that data, we train a random forest[28] to predict the ecosystem service value based on the area covered by each PFT within the geographic location of the study. Such random forest is used to calculate x_{PFT} values for each country, given by the normalized magnitude of the random forest prediction changing one by one the PFT-covered area to match the country's average value.

The country-level x_{PFT} values are used to calculate natural capital estimates iteratively for each country based on the PFTs shifts modeled by the LPJ-Guess dynamic terrestrial model under SSP2-4.5 with fixed socioeconomics (no land-use change policies) and using climate drivers from 4 different Earth system models: HadGEM2[29], GFDL[30], IPSL-CM5[31], and MIROC5[32]. These projections are part of the simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project[17] (ISIMIP), which allows retrieving the ecosystemic impacts of climate change in a framework consistent with other sectoral assessments done within the same framework. Therefore we create a time-series of country-level natural capital and temperature change, from which we obtain a damage function fitting the following quadratic function of temperature change

$$nN_{c,t} = nN_{c,0}\theta_c(\Delta T)^2 \qquad \text{eq 7}$$

The mean value of the theta estimates over the four climate model runs are reported on the Supplementary Table 2. We repeat this methodology for the market natural capital (eN), only changing the observations used from the VGS database to reflect either market or non-market values.

References

1. Pecl, G. T. *et al.* Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science* **355**, eaai9214 (2017).
2. Lenoir, J. & Svenning, J.-C. Climate-related range shifts – a global multidimensional synthesis and new research directions. *Ecography* **38**, 15–28 (2015).
3. Pörtner, H. O. *et al.* Scientific outcome of the IPBES-IPCC co-sponsored workshop on biodiversity and climate change. (2021).
4. World Bank. *The Changing Wealth of Nations 2021: Managing Assets for the Future*. (World Bank, 2021). doi:10.1596/978-1-4648-1590-4.
5. UN, E., FAO, I. & OECD, W. System of Environmental-Economic Accounting 2012: Central Framework. *New York: United Nations* (2014).
6. Arrow, K. J., Dasgupta, P., Goulder, L. H., Mumford, K. J. & Oleson, K. Sustainability and the measurement of wealth. *Environment and development economics* **17**, 317–353 (2012).
7. Barbier, E. B. The concept of natural capital. *Oxford Review of Economic Policy* **35**, 14–36 (2019).
8. Dasgupta, P. *The Economics of Biodiversity: the Dasgupta Review.* (HM Treasury, 2021).
9. Nordhaus, W. Estimates of the social cost of carbon: concepts and results from the

DICE-2013R model and alternative approaches. *Journal of the Association of Environmental and Resource Economists* **1**, 273–312 (2014).

10. Hope, C. The PAGE09 integrated assessment model: A technical description. *Cambridge Judge Business School Working Paper* 44 (2011).

11. Tol, R. & Anthoff, D. The Climate Framework for Uncertainty, Negotiation and Distribution (FUND), Technical Description, Version 3.9. *FUND Model* http://www.fund-model.org/versions/ (2014).

12. Bastien-Olvera, B. A. & Moore, F. C. Climate Impacts on Natural Capital: Consequences for the Social Cost of Carbon. *Annual Review of Resource Economics, Forthcoming* (2021).

13. Solow, R. M. A contribution to the theory of economic growth. *The quarterly journal of economics* **70**, 65–94 (1956).

14. Seidl, R. *et al.* Forest disturbances under climate change. *Nature climate change* **7**, 395–402 (2017).

15. Becknell, J. M. *et al.* Assessing Interactions Among Changing Climate, Management, and Disturbance in Forests: A Macrosystems Approach. *BioScience* **65**, 263–274 (2015).

16. Smith, B., Prentice, I. C. & Sykes, M. T. Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space. *Global ecology and biogeography* **10**, 621–637 (2001).

17. Frieler, K. *et al.* Assessing the impacts of 1.5 °C global warming – simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b). *Geoscientific Model Development* **10**, 4321–4345 (2017).

18. Jacobsen, J. B. & Hanley, N. Are there income effects on global willingness to pay for biodiversity conservation? *Environmental and Resource Economics* **43**, 137–160 (2009).

19. Johnson, J. A. *et al. The Economic Case for Nature: A global Earth-economy model to assess development policy pathways*. (World Bank, 2021).

20. Meinshausen, M. *et al.* Realization of Paris Agreement pledges may limit warming just below 2 °C. *Nature* **604**, 304–309 (2022).

21. World Bank. Wealth Accounts | DataBank. https://databank.worldbank.org.

22. Brandt, N., Schreyer, P. & Zipperer, V. Productivity measurement with natural capital. *Review of Income and Wealth* **63**, S7–S21 (2017).

23. Dasgupta, P. Measuring the wealth of nations. *Annu. Rev. Resour. Econ.* **6**, 17–31 (2014).

24. Fenichel, E. P. & Abbott, J. K. Natural Capital: From Metaphor to Measurement. *Journal of the Association of Environmental and Resource Economists* **1**, 1–27 (2014).

25. World Bank. *Where Is the Wealth of Nations?* (2006).

26. Lange, G.-M., Wodon, Q. & Carey, K. *The changing wealth of nations 2018: Building a sustainable future*. (The World Bank, 2018).

27. Managi, S. & Kumar, P. *Inclusive Wealth Report 2018*. (Taylor & Francis, 2018). doi:10.4324/9781351002080.

28. Breiman, L. Random Forests. *Machine Learning* **45**, 5–32 (2001).

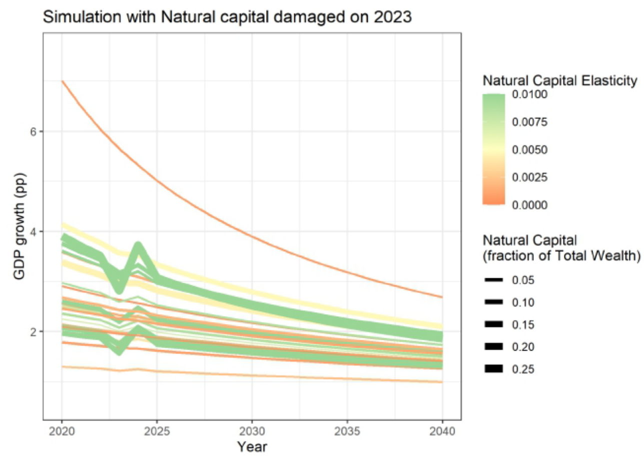
29. The HadGEM2 Development Team: G. M. Martin *et al.* The HadGEM2 family of Met Office Unified Model climate configurations. *Geoscientific Model Development* **4**, 723–757 (2011).

30. The GFDL Earth System Model Version 4.1 (GFDL‐ESM 4.1): Overall Coupled Model Description and Simulation Characteristics - Dunne - 2020 - Journal of Advances in Modeling Earth Systems - Wiley Online Library. https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019MS002015.

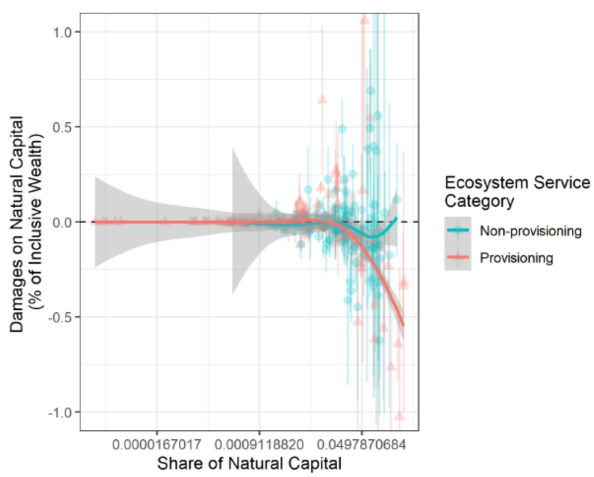
31. Climate change projections using the IPSL-CM5 Earth System Model: from CMIP3 to CMIP5 | SpringerLink. https://link.springer.com/article/10.1007/s00382-012-1636-1.

32. Watanabe, M. *et al.* Improved Climate Simulation by MIROC5: Mean States, Variability, and Climate Sensitivity. *Journal of Climate* **23**, 6312–6335 (2010).

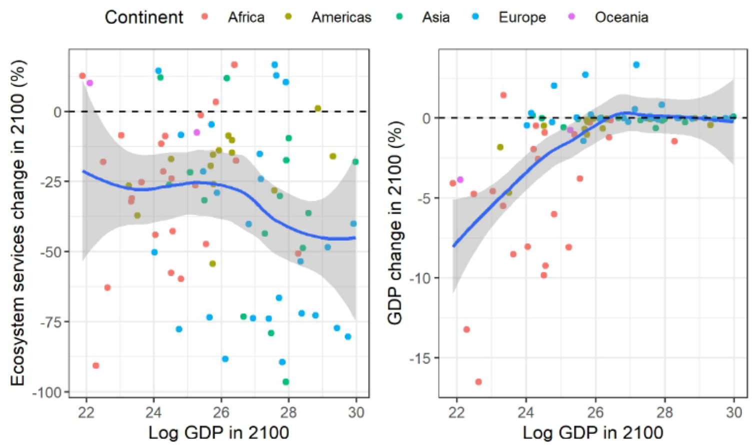
Supplementary Figures



Supp Fig 1. Economic effects of a 10% damage on natural capital in the year 2023 and subsequent rebound. The response of the economies in the Americas is modulated by the amount of natural capital and the production elasticity of natural capital.



Supplementary Figure 2. Damages on natural capital and share of natural capital in total wealth under SSP2-4.5 at 2.6°C of warming by 2100.



Supplementary Figure 3. Changes in ecosystem services (left) and GDP (right) by 2100 under SSP2-4.5 with respect to the baseline scenario.

Supplementary Tables

Supplementary table 1. Regression table of the production elasticities of a Cobb-Douglas production function, using the World Bank inclusive wealth accounts dataset.

	Log(GDP)		
	(1)	(2)	(3)
log(K)	0.248^{***}	0.238^{***}	0.249^{***}
	(0.009)	(0.031)	(0.009)
Log(H)	0.538^{***}	0.542^{***}	0.538^{***}
	(0.009)	(0.039)	(0.009)
Log(eN)	0.018^{***}	0.019^{**}	0.019^{***}
	(0.005)	(0.006)	(0.005)
Log(Nagg)			-0.005
			(0.007)
Observations	3,374	3,374	3,374
R^2	0.999	0.999	0.999
Adjusted R^2	0.999	0.999	0.999
Weighted by GDP	Yes	No	Yes
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Residual Std. Error	0.393 (df = 3205)	0.080 (df = 3205)	0.393 (df = 3204)
Note:			*p**p***p<0.01

Supplementary Table 2. Wealth, elasticities and damage coefficients used for the economic growth simulations.

country	year	H 2014 US$	K 2014 US$	eN 2014 US$	γ_1 (elasticity to H)	γ_3 (elasticity to eN)	γ_2 (elasticity to K)	DamCoeff_T2	DamCoeff_T2_sd
ALB	2018	8.12E+10	8.48E+10	6.03E+08	0.538339	0.0017	0.459961	-0.02469	0.039107
ARE	2018	2.28E+12	1.2E+12	17362323	0.538339	8.93E-07	0.46166	-0.03899	0.005957
ARG	2018	3.16E+12	1.6E+12	1.17E+10	0.538339	0.001501	0.46016	0.011685	0.00296
ARM	2018	8.49E+10	5.1E+10	6.75E+08	0.538339	0.002638	0.459023	0.006416	0.021874
AUS	2018	1.18E+13	7.58E+12	4.38E+10	0.538339	0.001818	0.459843	0.008653	0.021796
AUT	2018	3.11E+12	2.39E+12	7.09E+09	0.538339	0.000766	0.460895	0.017405	0.003971
AZE	2018	8.32E+10	1.14E+11	1.87E+08	0.538339	0.000192	0.461469	-1.25E-05	0.010157
BDI	2018	3.93E+10	5.76E+09	9.82E+08	0.538339	0.110535	0.351126	-0.01158	0.006151
BEL	2018	3.64E+12	2.63E+12	2.38E+09	0.538339	0.000189	0.461472	-0.04752	0.009027
BEN	2018	1.49E+11	4.07E+10	4.67E+09	0.538339	0.023251	0.43841	-0.00617	0.003357
BFA	2018	8.51E+10	3.83E+10	1.33E+10	0.538339	0.048449	0.413212	-0.00252	0.006635
BGD	2018	2.09E+12	8.63E+11	1.15E+09	0.538339	0.000828	0.460833	-0.00747	0.008837
BGR	2018	4.4E+11	1.96E+11	3.57E+09	0.538339	0.002419	0.459242	0.007362	0.012345
BHR	2018	1.43E+11	1.51E+11	726514.1	0.538339	3.85E-06	0.461658	NA	NA
BIH	2018	8.66E+10	5.95E+10	2.49E+09	0.538339	0.00568	0.455982	-0.0038	0.009407

BLR	2018	3.87E+11	2.92E+11	1.18E+10	0.538339	0.011431	0.45023	0.025363	0.02813
BLZ	2018	7.58E+09	4.92E+09	1.83E+08	0.538339	0.003591	0.458071	-0.00262	0.012436
BOL	2018	2.85E+11	8.31E+10	4.1E+09	0.538339	0.004991	0.45667	-0.00467	0.000864
BRA	2018	1.54E+13	6.56E+12	2.87E+11	0.538339	0.008192	0.45347	-0.00539	0.002119
BWA	2018	9.33E+10	6.44E+10	1.54E+09	0.538339	0.002537	0.459124	0.031507	0.005511
CAF	2018	4.44E+09	1.13E+10	5.92E+09	0.538339	0.107745	0.353917	-0.0031	0.00261
CAN	2018	1.98E+13	8.76E+12	3.25E+10	0.538339	0.000616	0.461046	-0.01942	0.008293
CHE	2018	6.78E+12	3.2E+12	1.83E+09	0.538339	0.000128	0.461533	0.00613	0.009563
CHL	2018	2.26E+12	1.02E+12	4.04E+10	0.538339	0.00802	0.453641	0.005998	0.002829
CHN	2018	1.78E+14	5.33E+13	3.22E+11	0.538339	0.000999	0.460662	0.007185	0.007069
CIV	2018	2.76E+11	1.02E+11	2.47E+10	0.538339	0.014103	0.447559	-0.00901	0.001061
CMR	2018	3.45E+11	1.11E+11	3E+10	0.538339	0.029556	0.432105	-0.00249	0.001346
COD	2018	3.65E+11	9.69E+10	1.59E+11	0.538339	0.090251	0.37141	-0.00576	0.001737
COG	2018	8.49E+10	9.47E+10	1.14E+10	0.538339	0.038468	0.423194	-0.00874	0.003222
COL	2018	2.77E+12	1.15E+12	1.15E+10	0.538339	0.001086	0.460575	-0.00372	0.000894
COM	2018	8.27E+09	6.06E+09	1.78E+08	0.538339	0.014639	0.447023	NA	NA
CRI	2018	6.01E+11	1.51E+11	1.42E+10	0.538339	0.009595	0.452066	-0.00526	0.011216

CZE	2018	1.54E +12	1.38E +12	9.51E +09	0.538 339	0.002 494	0.459 167	-0.00176	0.004905
DEU	2018	3.17E +13	2.14E +13	3.11E +10	0.538 339	0.000 382	0.461 279	-0.00971	0.007335
DJI	2018	1.27E +10	5.62E +09	64268 43	0.538 339	0.002 652	0.459 009	0.023264	0.019866
DNK	2018	2.83E +12	1.76E +12	1.63E +09	0.538 339	0.000 186	0.461 475	0.010187	0.001803
DO M	2018	5.56E +11	2.73E +11	9.27E +08	0.538 339	0.000 363	0.461 299	-0.00837	0.016736
ECU	2018	1.17E +12	4.9E+ 11	8.71E +09	0.538 339	0.003 165	0.458 496	-0.00234	0.002106
EGY	2018	1.28E +12	3.45E +11	1.9E+ 08	0.538 339	0.001 506	0.460 155	0.002699	0.038803
ESP	2018	9.28E +12	6.83E +12	8.79E +09	0.538 339	0.000 288	0.461 374	-0.01991	0.004904
EST	2018	2.08E +11	1.3E+ 11	5.99E +09	0.538 339	0.009 971	0.451 691	0.021417	0.009292
ETH	2018	8.14E +11	2E+11	1.62E +10	0.538 339	0.058 524	0.403 137	-0.00201	0.014056
FIN	2018	1.89E +12	1.38E +12	2.22E +10	0.538 339	0.004 121	0.457 541	0.110892	0.068662
FRA	2018	2.28E +13	1.51E +13	2.28E +10	0.538 339	0.000 332	0.461 329	-0.02114	0.007166
GAB	2018	4.05E +10	4.77E +10	1.01E +10	0.538 339	0.025 471	0.436 19	-0.00273	0.001266
GBR	2018	2.17E +13	1.11E +13	3.87E +09	0.538 339	7.01E -05	0.461 591	-0.01462	0.008401
GE O	2018	6.74E +10	8.46E +10	2.91E +08	0.538 339	0.000 736	0.460 925	-0.00104	0.003863
GHA	2018	5.34E +11	2.62E +11	5.54E +10	0.538 339	0.036 432	0.425 229	-0.00622	0.003902
GIN	2018	8.29E +09	3.16E +10	2.25E +10	0.538 339	0.055 611	0.406 05	-0.00898	0.006368

GMB	2018	1.13E+10	3.64E+09	1.68E+09	0.538339	0.025547	0.436115	-0.00163	0.019794
GRC	2018	9.62E+11	1.31E+12	6.14E+08	0.538339	0.00012	0.461541	-0.01092	0.013752
GTM	2018	4.05E+11	1.67E+11	6.75E+09	0.538339	0.008081	0.45358	-0.00252	0.012718
GUY	2018	1.91E+10	1.05E+10	5.87E+09	0.538339	0.042719	0.418943	-0.00919	0.006662
HND	2018	1.79E+11	8.17E+10	7.85E+09	0.538339	0.010723	0.450938	0.000591	0.016896
HRV	2018	3.35E+11	2.7E+11	3.71E+09	0.538339	0.002525	0.459136	-0.04386	0.0148
HTI	2018	5.11E+10	6.62E+10	2.6E+08	0.538339	0.004503	0.457159	-0.00649	0.01325
HUN	2018	9.79E+11	7.54E+11	3.7E+09	0.538339	0.000965	0.460697	0.001311	0.014522
IDN	2018	7.09E+12	4.56E+12	1.11E+11	0.538339	0.005052	0.45661	-0.00494	0.001834
IND	2018	2.12E+13	8.3E+12	5.87E+10	0.538339	0.001499	0.460162	-0.00335	0.00994
IRL	2018	1.73E+12	1.11E+12	1.13E+09	0.538339	0.000169	0.461492	-0.02299	0.00904
IRN	2018	2.07E+12	2.16E+12	1.14E+09	0.538339	6.97E-05	0.461592	0.018564	0.013975
IRQ	2018	6.54E+11	3.97E+11	2.51E+08	0.538339	3.01E-05	0.461631	-0.0211	0.003026
ISL	2018	2.23E+11	1.17E+11	1551818	0.538339	1.90E-06	0.461659	-0.01286	0.076692
ITA	2018	1.16E+13	1.09E+13	5.51E+09	0.538339	0.000103	0.461559	-0.00581	0.002845
JAM	2018	1E+11	1.07E+11	7.94E+08	0.538339	0.00175	0.459911	-0.00074	0.009893
JOR	2018	1.74E+11	1.67E+11	71744563	0.538339	0.000177	0.461485	-0.01428	0.018167

JPN	2018	3.83E+13	2.91E+13	1.96E+10	0.538339	0.000253	0.461408	0.025163	0.003521
KAZ	2018	8.71E+11	5.99E+11	1.73E+08	0.538339	5.14E-05	0.46161	0.08409	0.036587
KEN	2018	7.84E+11	1.83E+11	4.15E+10	0.538339	0.013167	0.448494	-0.00476	0.002502
KGZ	2018	3.5E+10	3.8E+10	24316306	0.538339	0.000129	0.461533	0.041855	0.022487
KHM	2018	1.85E+11	5.43E+10	9.24E+09	0.538339	0.008721	0.45294	-0.00289	0.006981
KOR	2018	1.05E+13	7.31E+12	5.53E+09	0.538339	0.000168	0.461494	-0.01639	0.011054
KWT	2018	4.48E+11	3.87E+11	7079528	0.538339	2.91E-06	0.461658	-0.0241	0.01695
LAO	2018	1.67E+11	4.88E+10	1.05E+10	0.538339	0.016462	0.445199	-0.00348	0.005153
LBN	2018	2.33E+11	1.81E+11	21471719	0.538339	9.35E-06	0.461652	0.008167	0.008703
LBR	2018	2.41E+10	9.08E+09	1.45E+10	0.538339	0.13686	0.324801	-0.00242	0.001741
LKA	2018	3.17E+11	3.33E+11	1.21E+09	0.538339	0.000673	0.460988	1.86E-06	0.007153
LSO	2018	2.12E+10	1.15E+10	2.14E+08	0.538339	0.032755	0.428906	-0.02312	0.015444
LTU	2018	3.26E+11	2.01E+11	4.15E+09	0.538339	0.003396	0.458265	0.013056	0.003525
LUX	2018	2.97E+11	2.04E+11	1.87E+08	0.538339	0.00013	0.461532	-0.03755	0.004906
LVA	2018	2.06E+11	2.33E+11	7.67E+09	0.538339	0.009805	0.451856	0.017093	0.01296
MAR	2018	5.06E+11	4.75E+11	4.94E+09	0.538339	0.001275	0.460387	-0.00469	0.011763
MDA	2018	1.82E+10	6.12E+10	6.83E+08	0.538339	0.002396	0.459266	0.017837	0.007658

MDG	2018	1.22E+11	3.84E+10	2.25E+10	0.538339	0.042888	0.418773	-0.00254	0.002176
MDV	2018	1.95E+10	1.24E+10	1051495	0.538339	2.58E-05	0.461636	NA	NA
MEX	2018	6.62E+12	5.52E+12	3.95E+10	0.538339	0.001157	0.460505	-0.00103	0.007371
MKD	2018	6.36E+10	4.66E+10	4.21E+08	0.538339	0.001422	0.460239	0.019376	0.022145
MLI	2018	8.08E+10	2.97E+10	3.56E+09	0.538339	0.022366	0.439295	0.009364	0.034485
MLT	2018	9.7E+10	3.73E+10	0	0.538339	0	0.461661	NA	NA
MNG	2018	6.36E+10	5.34E+10	7.1E+08	0.538339	0.001627	0.460034	0.026017	0.003986
MOZ	2018	1.05E+11	3.99E+10	3.09E+10	0.538339	0.069427	0.392234	-0.00851	0.004885
MRT	2018	4.09E+10	2.67E+10	3.02E+08	0.538339	0.012894	0.448767	0.001338	0.058095
MUS	2018	6.16E+10	3.99E+10	7476567	0.538339	2.38E-05	0.461638	NA	NA
MWI	2018	5.64E+10	1.47E+10	1.26E+10	0.538339	0.070935	0.390726	-0.00867	0.005518
MYS	2018	3.73E+12	1.02E+12	1.52E+11	0.538339	0.020506	0.441155	-0.00295	0.001241
NAM	2018	1.12E+11	3.2E+10	2.47E+09	0.538339	0.004565	0.457096	0.02672	0.012452
NER	2018	6.46E+10	4.92E+10	5.93E+08	0.538339	0.045858	0.415803	0.047659	0.058105
NGA	2018	3.72E+12	1.13E+12	3.47E+10	0.538339	0.011327	0.450335	-0.00823	0.002376
NIC	2018	8.4E+10	6.16E+10	5.81E+09	0.538339	0.012877	0.448784	-0.00325	0.011517
NLD	2018	7.12E+12	4.01E+12	1.05E+09	0.538339	5.82E-05	0.461603	-0.02687	0.019799

NOR	2018	2.84E+12	2.19E+12	4.54E+09	0.538339	0.000527	0.461134	-0.0043	0.025668
NPL	2018	1.89E+11	1.25E+11	5.36E+09	0.538339	0.004752	0.456909	0.018074	0.004851
OMN	2018	3.6E+11	2.41E+11	2156588	0.538339	1.23E-05	0.461649	0.032334	0.033889
PAK	2018	2.47E+12	6.27E+11	1.7E+09	0.538339	0.001138	0.460523	0.043271	0.023885
PAN	2018	3.34E+11	2.51E+11	1.55E+09	0.538339	0.000985	0.460676	-0.00371	0.007117
PER	2018	1.54E+12	7.32E+11	9.07E+09	0.538339	0.001279	0.460382	0.000538	0.002451
PHL	2018	2.62E+12	9.03E+11	1.95E+10	0.538339	0.00202	0.459641	-0.0022	0.004775
PNG	2018	1.31E+11	5.02E+10	1.45E+10	0.538339	0.023698	0.437964	-0.00242	0.0025
POL	2018	3.79E+12	1.55E+12	2.4E+10	0.538339	0.002041	0.45962	0.017133	0.007093
PRT	2018	1.51E+12	1.25E+12	7.34E+09	0.538339	0.001389	0.460272	-0.01822	0.010437
PRY	2018	3.89E+11	9.98E+10	1.35E+10	0.538339	0.014273	0.447389	-0.00585	0.003207
PSE	2018	5.23E+10	6.19E+10	0	0.538339	0	0.461661	NA	NA
QAT	2018	5.56E+11	7.58E+11	4778443	0.538339	5.58E-07	0.461661	-0.03812	0.052721
ROU	2018	1.45E+12	7.87E+11	9.82E+09	0.538339	0.001759	0.459902	0.027169	0.008673
RUS	2018	8.82E+12	1.12E+13	1.19E+11	0.538339	0.003618	0.458043	0.020063	0.007542
RWA	2018	8.9E+10	1.94E+10	4.67E+09	0.538339	0.042934	0.418728	-0.00098	0.010693
SAU	2018	2.46E+12	2.32E+12	2.76E+08	0.538339	7.66E-06	0.461654	-0.01947	0.02011

SEN	2018	1.41E+11	7.18E+10	1.16E+10	0.538339	0.016113	0.445549	-0.02349	0.02434
SGP	2018	2.62E+12	1.16E+12	32749359	0.538339	1.89E-06	0.46166	NA	NA
SLB	2018	1.2E+10	1.04E+09	6.48E+09	0.538339	0.21826	0.243401	-0.00209	0.005208
SLE	2018	3.43E+10	8.56E+09	8.59E+09	0.538339	0.071653	0.390009	-0.00497	0.004447
SLV	2018	1.54E+11	7.82E+10	1.44E+09	0.538339	0.006558	0.455104	-0.00454	0.026288
SUR	2018	9.54E+09	2.3E+10	1.25E+09	0.538339	0.03033	0.431331	-0.0072	0.00577
SVK	2018	7.11E+11	4.23E+11	5.49E+09	0.538339	0.002516	0.459145	0.011751	0.004081
SVN	2018	4.12E+11	2.62E+11	2.74E+09	0.538339	0.002321	0.45934	0.001052	0.021194
SWE	2018	4.43E+12	2.9E+12	2.7E+10	0.538339	0.002556	0.459105	0.042882	0.034977
SWZ	2018	3.51E+10	9.7E+09	3.41E+09	0.538339	0.029247	0.432414	0.015048	0.006571
TCD	2018	7.05E+10	2.69E+10	8.15E+09	0.538339	0.040671	0.420991	0.006513	0.031447
TGO	2018	7.1E+10	2.15E+10	1.08E+09	0.538339	0.038785	0.422876	-0.00642	0.00084
THA	2018	3.41E+12	1.62E+12	2.68E+10	0.538339	0.004	0.457662	-0.00306	0.004971
TJK	2018	4.03E+10	1.72E+11	77717231	0.538339	0.010359	0.451302	0.057737	0.036209
TKM	2018	2.37E+11	1.98E+11	0	0.538339	5.20E-06	0.461656	NA	NA
TTO	2018	1.13E+11	3.13E+10	3.24E+08	0.538339	0.000687	0.460974	-0.01519	0.011089
TUN	2018	1.93E+11	1.45E+11	8.76E+08	0.538339	0.002142	0.45952	-0.0067	0.017938

TUR	2018	9.23E+11	2.58E+12	1.2E+10	0.538339	0.00095	0.460711	0.028984	0.018478
TZA	2018	5.27E+11	1.87E+11	4.41E+10	0.538339	0.023642	0.438019	-0.00613	0.003087
UGA	2018	3.25E+11	7.79E+10	2.65E+09	0.538339	0.079105	0.382557	-0.00715	0.009823
UKR	2018	7.46E+11	1.45E+12	1.05E+10	0.538339	0.003572	0.458089	0.012356	0.013781
URY	2018	4.64E+11	2.54E+11	8.64E+09	0.538339	0.021224	0.440438	-0.00331	0.005751
USA	2018	2.03E+14	8.62E+13	1.89E+11	0.538339	0.000345	0.461316	0.009009	0.00332
VEN	2018	4.97E+12	7.71E+11	5.2E+09	0.538339	0	0.461661	-0.00464	0.003879
VNM	2018	2.19E+12	5.27E+11	9.39E+10	0.538339	0.018036	0.443626	-0.00503	0.004111
YEM	2018	7.84E+10	5.74E+11	4.66E+08	0.538339	0.000497	0.461164	0.06658	0.086846
ZAF	2018	2.12E+12	1.17E+12	5.55E+10	0.538339	0.007042	0.454619	0.005019	0.006548
ZMB	2018	2.53E+11	1.24E+11	4.27E+10	0.538339	0.049308	0.412354	-0.01354	0.005806
ZWE	2018	2.26E+11	5.96E+10	1.55E+10	0.538339	0.016638	0.445023	0.034582	0.02349

Chapter 3

Persistent Effect of Temperature on GDP Identified from Lower Frequency Temperature Variability

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Persistent Effect of Temperature on GDP Identified from Lower Frequency Temperature Variability

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Persistent Effect of Temperature on GDP Identified from Lower Frequency Temperature Variability

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Abstract

It is well established that temperature variability affects a range of outcomes relevant to human welfare, including health (Gasparrini et al., 2017) emotion and mood (Baylis et al., 2018), and productivity across a number of economic sectors (Carleton & Hsiang, 2016; Dell et al., 2014). However, a critical and still unresolved empirical question is whether temperature variation has a long-lasting effect on economic productivity and, therefore, whether damages compound over time in response to long-lived changes in temperature expected with climate change. Several studies have identified a relationship between temperature and GDP (Burke et al., 2015; Dell et al., 2012; Kalkuhl & Wenz, 2020), but empirical evidence as to the persistence of these effects is still weak. This paper presents a novel approach to isolate the persistent component of temperature effects on output using lower frequency temperature variation. Using three different datasets we find that longer temperature anomalies affect GDP growth as much or more than short-lived anomalies, implying persistent and therefore cumulative effects of climate change on economic output. The population-weighted global effect of -0.8 pp per degree is sufficient to reduce per-capita income in 2100 by 44% under RCP6, approximately an order of magnitude larger than damages currently represented in cost-benefit integrated assessment models (Diaz & Moore, 2017).

A large body of evidence now exists showing a relationship between temperature fluctuations and economic productivity. Temperature has been shown to influence output at global (Burke et al., 2015; Dell et al., 2012), national (Deryugina & Hsiang, 2017; Schlenker & Roberts, 2009), and regional scales (Kalkuhl & Wenz, 2020), affecting a wide range of sectors in both rich and poor countries. The persistence of these impacts has first-order implications for the magnitude of climate change damages: if temperature fluctuations affect the determinants of economic growth then they have a persistent impact on the level of economic output. In this case climate change damages are cumulative and may be orders of magnitude larger than currently represented in models used for the cost-benefit analysis of climate change, which mostly assume non-persistent damages (Dietz & Stern, 2015; Moore & Diaz, 2015; Moyer et al., 2014).

Despite its importance for determining the aggregate costs of climate change, evidence on the persistence of the impacts of temperature shocks is sparse and contradictory. Dell, Jones and Olken (2012) show that non-persistent impacts to output and persistent impacts to growth can produce identical

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contemporaneous effects, but can be distinguished using lagged temperature effects. Using global national accounts data, they fit a reduced-form model with lagged temperature terms and find evidence that effects of temperature shocks in poorer countries persist for at least 10 years, implying large negative effects of higher temperatures for economic growth, at least in the medium-term. Using a similar dataset, Burke, Hsiang and Miguel (2015) find robust evidence for a non-linear, hill-shaped relationship between contemporaneous temperature and GDP growth, but evidence for persistent impacts to the economy is weaker since the sum of lagged effects has large standard errors with confidence intervals that overlap zero. In a model-selection exercise based on cross-validation, Newell, Prest and Sexton (2020) show total climate damages are highly sensitive to the question of persistence, and to the functional form of empirical models used to estimate effects. At a smaller spatial scale, Deryugina & Hsiang (2017) found evidence of persistent but declining effects during the first 10 years after a temperature shock in individual U.S. counties, and Colacito et al. (2019) found that increases in summer and fall temperature could have persistent effects on gross state product of U.S. states.

A major empirical challenge is that estimating the sum of lagged effects, particularly for a non-linear function, can produce large standard errors and therefore high uncertainty. For instance, in the quadratic specification used by Burke, Hsiang and Miguel (2015), identifying cumulative effects over 10 years requires estimating and summing 20 regression coefficients. The uncertainty in this statistic depends on the variance and covariance of all 20 parameter estimates. More recent empirical investigations of climate impacts on economic growth have focused on resolving detail at the subnational scale (Colacito et al., 2018; Damania et al., 2020; Kalkuhl & Wenz, 2020), or on resolving impacts on the production process (Letta & Tol, 2019). While these suggest some persistence in temperature effects, this key question relevant for understanding the aggregate costs of climate change remains largely unresolved.

Approach

Here we propose a statistical test to differentiate between persistent effects of temperature on growth and temporary effects of temperature on output using lower-frequency temperature variation. We first use a simulation exercise to demonstrate the discriminatory power of the test. Second, we implement this test on individual country-level time-series of temperature and economic growth, and finally and characterize the aggregate evidence for growth vs levels effects.

The essence of the approach is that persistent and transient impacts to economic output can be distinguished using temperature variation occurring at different frequencies. Internal variability of the climate system gives rise to oscillations at different timescales. This is an intrinsic characteristic of non-linear dynamic systems like the Earth's climate (Lorenz, 1963). While some of these fluctuations such as the El Nino Southern Oscillation with a period of 2 to 7 years are well understood (e.g. Imbers et al., 2013), spectral analysis of atmospheric time series reveal fluctuations at all possible frequencies (Hasselmann, 1976; Mann et al., 2020) Figure 1a shows this variability in the US temperature time series between 1960 and 2017 (Matsuura & Willmott, 2018a, 2018b). We use a low-pass filter to successively remove high-frequency variation and obtain temperature time series that preserve only lower-frequency oscillations.

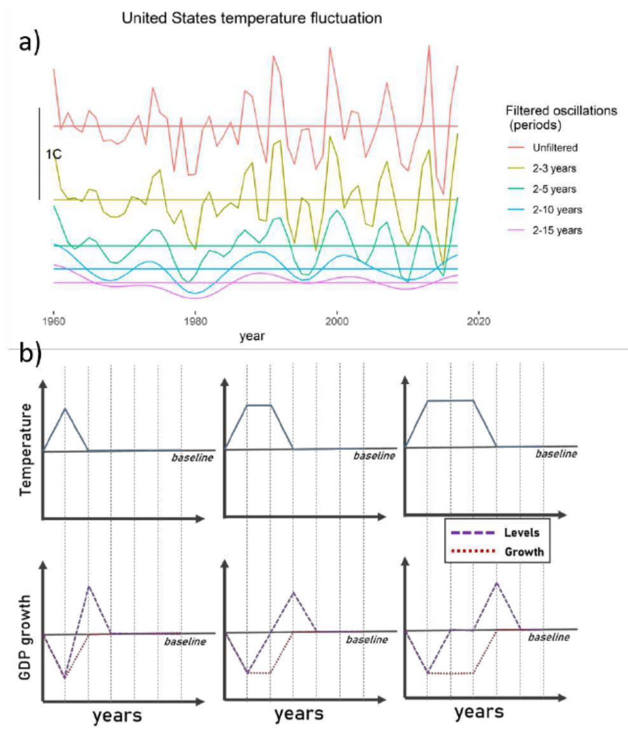

Fig 1. Temperature fluctuations and its effects at different frequencies. a) US population-weighted temperature fluctuations after detrending and filtering higher-frequency variation (Matsuura & Willmott, 2018a). The top, orange line shows the US temperature time series. Lower lines show the filtered time series, removing successively more higher-frequency variation. We spread the time-series across y-axis for visual purposes only but in reality all time-series oscillate around zero because they were demeaned and de-trended before filtering. b) Temperature shocks at decreasing frequencies are shown in the upper panels while the effects of those shocks on GDP growth, under both the levels and growth models, are given in the lower panels.

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Temperature variability at different timescales would be expected to produce distinct economic dynamics depending on the persistence of economic impacts. This is illustrated in Figure 1b, which shows the change in GDP growth that would be expected under temperature shocks of different durations and alternate models of economic impact. Dell et al. (2012) derive a simple equation for a model that includes both non-persistent levels impacts (β) and persistent growth impacts (γ), given baseline growth rate g:

$$g_t = g + (\beta + \gamma)T_t - \beta T_{t-1} \tag{1}$$

Where T_t is the deviation in temperature from some mean value in period t. Figure 1b illustrates how the timescale of temperature variation interacts with the models of economic impact, using two extreme cases. In the "levels model" we set the growth effect to zero (i.e. $\gamma = 0$) so that:

$$g_t = g + \beta(T_t - T_{t-1}) = g + \beta \Delta T_t \tag{2}$$

In the "growth model", we set the level effect to zero (i.e. $\beta = 0$) so that:

$$g_t = g + \gamma T_t \tag{3}$$

For one period temperature shocks, the contemporaneous effect of temperature on economic growth is the same under the two scenarios (Figure 1b, left panel). However, for longer temperature excursions, there are time periods where $\Delta T_t = 0$ but $T_t > 0$, causing the two impact models to produce divergent predictions. In particular, effects on growth continue under long temperature excursions, whereas initial effects in the levels model subsequently attenuate to zero (Figure 1b, right panel).

This means that it should be possible, in principle, to distinguish these two cases in empirical data using different timescales of temperature variability. It is a common practice in signal processing problems to decompose time series into a sum of periodic components with varying frequencies, amplitudes and phases (Duhamel & Vetterli, 1990), widely used in a variety of fields like audio processing, electrical engineering, and climate science (Bergland, 1969; Ghil, 2002; Smith, 2007). This approach allows the time-series to be reconstructed using a specific subsets of desired frequencies. A low-pass filter is a version of the time series that only preserves low frequency components. Following studies in the climate literature (e.g. Mann et al., 2014), we use a low-pass filter to remove inter-annual variations and obtain temperature time series that preserve only lower-frequency oscillations. If temperature shocks affect output but not the underlying growth rate, the estimated effect using only longer period temperature changes on GDP growth, should be smaller than that estimated using the unfiltered time series. In contrast, if temperature shocks have a persistent effect on growth, then the estimated effect will not vary with the frequency of temperature variation used for estimation.

Figure 2 demonstrates this effect in a simulation exercise. This shows results from time series regressions of simulated economic growth on simulated temperature at different levels of filtering under two cases – one in which temperature affects only the level of output (purple line) and one in which it affects the growth rate (pink line). The random temperature time series used in the simulations preserve the frequency distribution of the Earth's natural oscillations by matching the spectral decomposition on 1500 years of pre-industrial global temperatures based on the Last Millennium Reanalysis (Tardif et al., 2019). Using this decomposition we generate 10,000 random 350 year temperature time-series that preserve this frequency distribution but with random phase shifts (e.g. Figwer, 1997) and then simulate economic dynamics for each temperature time series under the two alternate impacts models, using equations 2 and 3 and adding an independent and identical distributed (iid) noise component. We regress the simulated economic growth data on temperature after filtering out varying ranges of frequencies from the temperature time series.

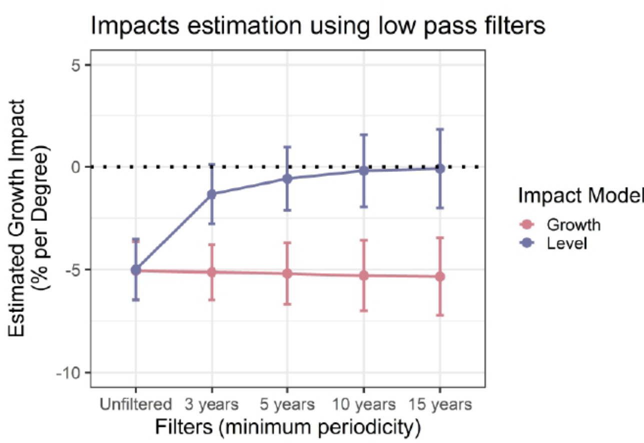

Figure 2. Simulation exercise demonstrating the divergence of regression results under increasing frequency filters under two alternate models of temperature impacts on economic production, a non-persistent "levels" model (purple) and a fully persistent "growth" model (pink).

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Figure 2 shows the mean value of the estimated coefficients and its standard error for all the simulations. Without any filtering using only contemporaneous temperatures, the two types of impacts are indistinguishable, as originally pointed out by Dell, Jones and Olken (Dell et al., 2012). But filtering out high frequencies in the temperature data produces divergent effects: the estimated effect under growth impacts remains constant while the coefficients in the levels case attenuate markedly. In other words, the divergence of the pink and purple lines in Figure 2 at lower frequencies, means that these two possible worlds – one with and one without persistent temperature impacts – could potentially be distinguished using this method.

The general approach of using lower frequency temperature variation to better understand the magnitude and dynamics of climate change impacts is well established in the climate impacts literature. Several papers contrast impacts estimated using high-frequency weather variation with those estimated using lower-frequency variation, either average temperature differences over long intervals (i.e. "long differences") or multi-decadal moving averages, to identify the effects of adaptation on the levels of climate damages (Burke & Emerick, 2016; Kolstad & Moore, 2020; Mérel & Gammans, 2021; Taraz, 2017). Most notably, Hsiang (2016) presents panel regressions of US temperature and corn yield data, successively filtering out higher-frequency temperature and yield variation and argues that the stability of regression estimates using longer temperature variation indicates agricultural adaptation to warming is either slow or ineffective.

While conceptually similar to our empirical approach, the question this literature addresses is distinct in that, because the dependent variable in each case is a level outcome (typically crop yields), these papers address how adaptation does or does not attenuate the *level* of climate damages as a function of the longevity of temperature variation. Since our dependent variable is a growth rate, the question addressed is whether the effect of short-term temperature shocks on the level of GDP persist, and therefore whether damages compound over time in response to sustained periods of warming. Most importantly, even if the estimated growth effect attenuates to zero at lower frequencies (i.e. the purple line in Figure 2), this is still consistent with an effect of long-term warming on the *level* of GDP, for instance as modeled in the damage function of most cost-benefit integrated assessment models (Diaz & Moore, 2017).

We use our test to investigate the persistence of temperature effects on economic production. We use GDP data from the World Bank covering 217 countries from 1961 to the present (World Bank, 2021), merging this dataset with population-weighted temperature and rainfall data from University of Delaware

(Matsuura & Willmott, 2018a, 2018b). To identify whether country-level temperature impacts have persistent effects we performed the following regression for each country:

$$g_t = \theta_f T_{t,f} + \pi_f P_{t,f} + \epsilon_t \tag{4}$$

Where $T_{t,f}$ and $P_{t,f}$ are the population-weighted temperature and rainfall in year t after filtering out frequencies lower than f. The filters f are low-pass filters that filter-out any oscillations with periods shorter than 3, 5, 10, and 15 years, or f=unfiltered when no filter was applied. The low-pass filter algorithm requires data that spans at least twice the upper bound periodicity, which results in some countries not having estimates for all the levels of filtering due to missing data at earlier time periods. Growth, temperature and rainfall data are all demeaned and detrended at the country-level prior to analysis.

Results

The behavior of the estimates θ_f for each country contains information about the persistence of temperature effects on the economy. Figure 3 shows the estimated values of θ_f for all countries at different levels of filters, binned into three broad categories: an intensifying effect, where the absolute value of θ_f increases at lower frequencies (left panel); a constant effect over different frequency filters (central panel); and a converging effect, where the absolute value of θ_f decreases at lower frequencies (right panel). We find that a large majority of countries (153 out of 176 where we found an estimate) have intensifying or constant effects using lower frequency temperature variability, consistent with a persistent effect of temperature on output, at least in the medium term (up to 15 years). 42 countries have lower-frequency estimates that are statistically different from zero at the 90% confidence level (of which 18 might be expected as false positives given the number of comparisons).

The majority of countries (117), show evidence for intensifying effects at lower frequencies, where the effect of each degree of warming becomes larger for longer temperature excursions. An intensifying effect might be due to adjustment dynamics whereby people and firms are able to better exploit beneficial opportunities (for positive effects) or gradually exhaust limited coping resources (for negative effects) in the face of longer-term temperature fluctuations. Another explanation would be if countries experience a combination of level and growth effects with opposite signs that partially offset each other in the unfiltered estimate, a pattern identified by Dell, Jones and Olken (2012) for some countries. A final explanation for this intensifying pattern is statistical: substantial measurement error in the temperature variable could attenuate the estimated coefficient, biasing it towards zero. Applying filters will gradually filter out noise in the temperature variable, producing larger coefficients closer to the true growth effect. A second simulation exercise demonstrates this effect but also shows the levels and growth cases to be distinguishable, even in the presence of measurement error (Supplementary Figure 1).

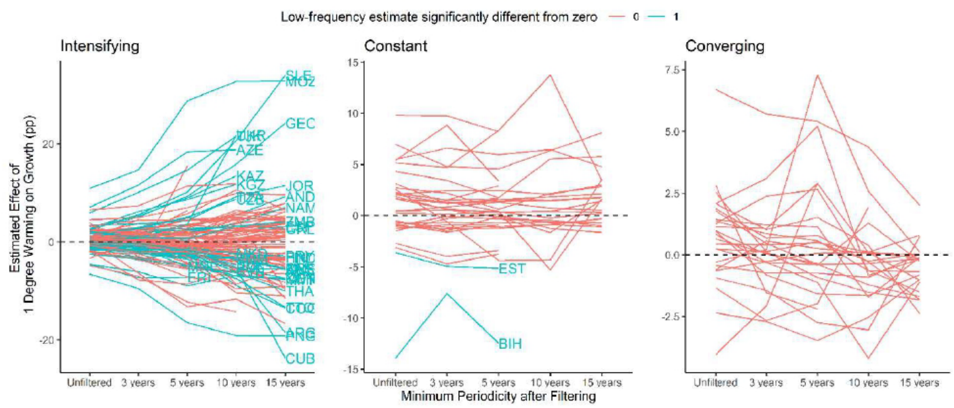

Fig 3. Country-level estimates of temperature effect on economic growth. Left panel: Those countries for which the absolute value of the lower-frequency estimate is 1.5 times larger than the magnitude of their unfiltered estimate. Middle panel: Those countries which low-frequency estimate does not diverge from the unfiltered estimate (criterion: low-frequency estimate within unfiltered estimate +/- half the raw estimate value). Right panel: All remaining countries.

We performed the same analysis using two alternative economic growth datasets that span a longer time period but include fewer countries. Firstly we used the Barro-Ursua dataset, with annual data on economic growth of 43 countries starting as early as 1790 to 2009, developed to examine the persistence of macro-economic shocks (Barro & Ursúa, 2008; Barro & Ursua, 2010). Secondly, we use the Maddison Project database that standardizes country-level GDP per capita for 170 countries, some of them back to the beginning of the Common Era, to 2018 (Bolt & van Zanden, 2020). Due to the sparsity of temperature and rainfall records pre-1900, we use only post-1900 data for both datasets. Supplementary Figure 2 replicates Figure 3 for these two alternate datasets covering different subsets of countries and much longer time-periods than the World Bank data. We again see evidence that most countries show constant or intensifying effects of temperature at lower frequency variability, rather than the converging coefficients associated with a levels effect of temperature on GDP.

We analyze the evidence for persistence across all countries at the global scale by pooling the estimate shown in Figure 3 and estimating the following regression model

$$|\theta_{f,c}| = F_f + \epsilon_{f,c} \tag{5}$$

Where the absolute value of the temperature coefficient estimate in country c at filtering level f $|\theta_{f,c}|$ is regressed on the level of filtering F, clustering standard errors at the continent level. If a non-persistent, levels effect were dominant, we would expect to see the absolute magnitudes of the filtered estimates converging towards zero, indicating a negative coefficient estimate on the filtering variables F. Table 1 shows the results of this regression model, and shows that, across all countries, we do not see evidence for this attenuating effect. Instead, like Figure 3, the regression results show evidence for an intensifying effect where the absolute value estimated using lower frequency temperature variation is larger than the value estimated using unfiltered data, as indicated by positive coefficients on the filtering variables in Table 1.

Supplementary Figure 3 examines whether the direction and persistence of temperature impacts is associated with either per capita GDP or mean temperature. We find no systematic differences in the estimated long-term temperature effect between rich and poor or cold and hot countries.

Figure 3 shows both positive and negative effects of warming in different countries, but the average global effect, weighting by both GDP and population, is negative. For short-term impacts, the combination of levels and growth effects has a population-weighted mean value of -0.007 percentage points (pp) per degree of warming, which intensifies to -0.8 pp per degree of warming, using the lowest frequency estimate.

Discussion

Here we show evidence that temperature shocks have historically had persistent effects on economic output across a broad range of countries. The question of the persistence of climate damages is a first order problem for climate change economics. Studies that model climate impacts on economic growth, tend to produce aggregate climate change cost an order of magnitude larger than studies modeling only levels impacts (Moore & Diaz, 2015; Ricke et al., 2018). This is because, in response to the permanent shifts in temperature expected with climate change, persistent impacts compound over time, producing far larger aggregate damages over the long time-frames relevant for assessing climate change costs.

	Dependent variable:					
	Absolute value of temperature coefficient					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.022***	0.013***	0.014***	0.010***	0.020***	0.013***
(dropped = Unfiltered)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Filter = 3 years	0.003	0.003***	0.002***	0.002***	0.004**	0.002
	(0.002)	(0.001)	(0.0005)	(0.0004)	(0.002)	(0.001)
Filter = 5 years	0.012***	0.009***	0.003*	0.004***	0.010***	0.006*
	(0.004)	(0.003)	(0.001)	(0.001)	(0.004)	(0.003)
Filter = 10 years	0.025***	0.019***	0.008***	0.007***	0.026***	0.016***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.006)	(0.005)
Filter = 15 years	0.031***	0.020***	0.011**	0.008**	0.027***	0.018***
	(0.006)	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)
Dataset	World Bank	World Bank	Barro	Barro	Maddison	Maddison
Observations	814	814	205	205	780	780
R^2	0.049	0.073	0.040	0.034	0.069	0.063
Adjusted R^2	0.044	0.068	0.021	0.015	0.064	0.058
Residual Std. Error	0.052	0.195	0.020	0.125	0.041	0.196
Weighting	None	Inverse SE	None	Inverse SE	None	Inverse SE
Number of countries	217	217	43	43	170	170
Years range	1961-2020	1961-2020	1900-2009	1900-2009	1900-2018	1900-2018
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 1. Results of regression model. Standard errors clustered at the continent level. Model 1 is unweighted, and Model 2 weights by the inverse of the standard deviation of the parameter $\theta_{f,c}$, the value of the estimated temperature coefficient at filter f in country c.

In contrast with previous literature that has mostly used high-frequency, year-to-year temperature variation to estimate climate impacts on the economy, here we use lower frequency variation. Our identification strategy focuses on the persistent effect of temperature by controlling for time-trends and country-specific dynamics (via demeaning and detrending) but uses multi-year temperature variability instead of lags to distinguish between growth and levels effects.

Applying this test to three different datasets of economic growth, we fail to find strong evidence of declining temperature effects at longer time horizons. For most countries, the estimated effects of temperature on the economy do not attenuate after filtering out high frequencies, and in many countries they instead intensify over time. Specifically, we found persistent temperature impacts on economic growth in 85% (68%; 87%) of the countries, out of which more than 78% (75%; 83%) have an estimate that intensifies in the medium-run using the World Bank (Barro-Ursua; Maddison Project) dataset. This intensifying dynamic might be due to adaptation or coping dynamics, changing effects of measurement error (See Supplementary Figure 1), or competing growth and levels effects with different signs. Whatever the explanation, the identification of effects that are both economically meaningful and, in some cases, statistically different from zero using only lower frequency temperature variation suggests a sensitivity of aggregate economic output to temperature shocks that persists over at least the 5-15 year time frame.

Like previous work, we find both positive and negative effects of temperature on different countries. Aggregating to the global level, we find net negative effects on both the average person (weighting by population) and the average dollar (weighting by GDP), with lowest-frequency estimates of -0.8 and -1.5 percentage point reduction in growth per degree of warming, respectively. This has large economic implications, for instance, the Shared Socioeconomic Pathway 2 (a middle-of-the-road scenario) projects that global income in 2100 will more than quadruple with respect to 2020, with an annual equivalent growth rate of 2%. Given temperature projections under RCP6, our aggregate population-weighted estimate suggests incomes in 2100 would be 43% lower with annual average income growth cut to 1.2%. For comparison, damages at a similar level of warming using damage functions in the three main integrated assessment models used to calculate the social cost of carbon are an order of magnitude smaller (Diaz & Moore, 2017).

While providing evidence of persistent impacts of temperature shocks on growth, our framework does not isolate the mechanisms by which they arise. Past studies have modeled persistent impacts as resulting from a slow-down in total factor productivity growth (Moore & Diaz, 2015; Moyer et al., 2014), changes to the capital depreciation rate (Moore & Diaz, 2015), or impacts to the stock of natural capital (Bastien-Olvera & Moore, 2021). Other studies leave the mechanism of growth rate impacts unspecified (Glanemann et al., 2020; Ricke et al., 2018). Letta & Tol (2019) investigate this question and suggest impacts arise through effects on total factor productivity growth, but more work is needed to understand exactly how these impacts manifest. Our findings show that in the long-term societies are sensitive to changes in climate and that the risk associated with climate change could be greatly underestimated if we overlook the persistent nature of impacts.

Methods

For the simulation exercise (Figure 2), we first generated 10,000 random 350-year temperature time series that preserve the internal dynamics and characteristic periodicity intrinsic to the climate system. This dynamic was retrieved by performing a fast Fourier transform (FFT) of 1500 years of global mean surface temperature data prior to anthropogenic influence, obtained from the Last Millennium Reanalysis project (Tardif et al., 2019). Simulated temperature time-series were generated using the spectral profile given by this FFT but with randomly chosen phases, generating 10,000 random counterfactual time series that might have arisen from the Earth's natural variability.

For each of the 10,000 temperature time series we generated two alternative economic growth time series that reflected the two climate impacts scenarios that we hope to distinguish: levels and growth. Following Dell et al. (2012), the levels model is given by $g_t = g + \beta T_t - \beta T_{t-1}$ and the growth model by $g_t = g + \gamma T_t$. The growth baseline g was set at 0.01 representing 1% per year baseline growth, the temperature coefficients β and γ were both set at -0.05 representing 5% decrease in growth per degree of warming, and a random noise was drawn from a normal distribution with standard deviation of 0.005, representing growth rate variability unexplained by temperature.

The persistence test consists of regressing growth on temperature after filtering the temperature time series to remove higher frequency oscillations. We use a low-pass filter in R (pass.filt from dplR library) that removes all oscillations with periodicity between 2 and the desired upper boundary of the filter. We perform the regressions of simulated growth on simulated temperature for 4 sets of filters (upper boundary = 3, 5, 10 and 15), and an unfiltered case. The unfiltered case, in both the simulations and the main regressions also includes a one-year temperature lag. This is required for generating an unbiased estimate of the levels effect - if temperature affects levels then T_{t-1} determines g_t (i.e. equation 2). Omitting T_{t-1} will therefore bias estimates of the effect of contemporaneous temperature shocks (T_t) if there is temporal autocorrelation in the timeseries. Lags are not included in regressions using filtered temperature data since these regressions are intended to integrate the effect of persistent temperature excursions. Figure 2 shows the mean value of the estimates after filtering the temperature data and the 95% confidence interval.

We retrieved yearly country-level data on economic growth for the 217 countries in the World Bank database (World Bank, 2021) for the period 1960 to 2020. Gridded temperature and precipitation data from the University of Delaware dataset (1900 to 2017;Matsuura & Willmott, 2018a, 2018b) was aggregated to the country level using 2015 population weighting from the Gridded Population of the World version 4 dataset (Doxsey-Whitfield et al., 2015). Alternative datasets that were used to check for the robustness of the results (See Supplementary Figure 2) were: 1) the Barro-Ursua economic dataset that covers 43 countries from the late 18th century to 2009 (Barro & Ursua, 2010), and 2) the Maddison Project economic dataset that covers a few countries starting in the 14th century, a dozen or so countries starting in the late 18th century, and more than 100 countries from 1950 to 2018 (Bolt & van Zanden, 2020). Although these economic growth datasets go back further, we limit analysis to the post-1900 period because of temperature and rainfall data availability.

Temperature, rainfall and economic growth data was demeaned and detrended by country to remove time-invariant country variation and long-term, country-specific weather and growth rate trends. The residuals after demeaning and detrending were used to estimate the temperature effect (θ) on economic growth by performing the following regression for each country: $g_t = \theta_f T_{t,f} + \pi_f P_{t,f} + \epsilon_t$ where the index (f) represents the level of filtering applied to the temperature and rainfall data before performing the regressions.

As shown by our simulation (Figure 2), the persistence test consists of identifying whether (θ) converges to zero after filtering higher frequencies. To characterize the behavior of θ we create three categories. The first category ("Intensifying") consists of those countries which absolute value of the estimate θ for the lowest frequency estimate is at least 50% larger than the absolute value of the estimate without filtering (i.e. $|\theta_{f=x}| \geq 1.5 * |\theta_{unfiltered}|$ where x is the highest level of filtering available for that country). The second category ("Constant") are countries in which the estimate remains constant ($0.5 * \theta_{unfiltered} \geq \theta_{f=x} \geq 1.5 * \theta_{unfiltered}$). The third category consists of the remaining countries, which estimate could be seen as converging to zero or even changing sign but without really having a significant long-term effect.

Estimates of future damages were computed using the average value of the global mean surface temperature projected by the models part of the Climate Model Inter-comparison Project 5 (Taylor et al., 2012), and the Shared Socioeconomic Pathway 2 base quantification (Fujimori et al., 2017).

References

Barro, R. J., & Ursúa, J. F. (2008). *Macroeconomic crises since 1870*. National Bureau of Economic Research.

Barro, R., & Ursua, J. (2010). *Barro-Ursua Macroeconomic Data*. https://scholar.harvard.edu/barro/publications/barro-ursua-macroeconomic-data

Bastien-Olvera, B. A., & Moore, F. C. (2021). Use and non-use value of nature and the social cost of carbon. *Nature Sustainability*, *4*(2), 101–108.

Baylis, P., Obradovich, N., Kryvasheyeu, Y., Chen, H., Coviello, L., Moro, E., Cebrian, M., & Fowler, J. H. (2018). Weather impacts expressed sentiment. *PloS One*, *13*(4), e0195750.

Bergland, G. (1969). Fast Fourier transform hardware implementations–An overview. *IEEE Transactions on Audio and Electroacoustics*, *17*(2), 104–108. https://doi.org/10.1109/TAU.1969.1162041

Bolt, J., & van Zanden, J. L. (2020). *Maddison style estimates of the evolution of the world economy. A new 2020 update*. 44.

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106–140.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*, 235–239. https://doi.org/10.1038/nature15725

Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, *353*(6304).

Colacito, Ric, Hoffmann, B., & Phan, T. (2018). *Temperatures and Growth: A Panel Analysis of the United States* (SSRN Scholarly Paper ID 2546456). Social Science Research Network. https://doi.org/10.2139/ssrn.2546456

Colacito, Riccardo, Hoffmann, B., & Phan, T. (2019). Temperature and growth: A panel analysis of the United States. *Journal of Money, Credit and Banking*, *51*(2–3), 313–368.

Damania, R., Desbureaux, S., & Zaveri, E. (2020). Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). *Journal of Environmental Economics and Management*, 102335.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, *52*(3), 740–798.

Deryugina, T., & Hsiang, S. (2017). *The Marginal Product of Climate* (No. w24072; p. w24072). National Bureau of Economic Research. https://doi.org/10.3386/w24072

Diaz, D., & Moore, F. (2017). Quantifying the economic risks of climate change. *Nature Climate Change*, *7*(11), 774–782.

Dietz, S., & Stern, N. (2015). Endogenous Growth, Convexity of Damage and Climate Risk: How Nordhaus' Framework Supports Deep Cuts in Carbon Emissions. *The Economic Journal*, *125*(583), 574–620. https://doi.org/10.1111/ecoj.12188

Doxsey-Whitfield, E., MacManus, K., Adamo, S. B., Pistolesi, L., Squires, J., Borkovska, O., & Baptista, S. R. (2015). Taking advantage of the improved availability of census data: A first look at the gridded population of the world, version 4. *Papers in Applied Geography*, *1*(3), 226–234.

Duhamel, P., & Vetterli, M. (1990). Fast fourier transforms: A tutorial review and a state of the art. *Signal Processing*, *19*(4), 259–299. https://doi.org/10.1016/0165-1684(90)90158-U

Figwer, J. (1997). A new method of random time-series simulation. *Simulation Practice and Theory*, *5*(3), 217–234. https://doi.org/10.1016/S0928-4869(96)00007-9

Fujimori, S., Hasegawa, T., Masui, T., Takahashi, K., Herran, D. S., Dai, H., Hijioka, Y., & Kainuma, M. (2017). SSP3: AIM implementation of shared socioeconomic pathways. *Global Environmental Change*, *42*, 268–283.

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Gasparrini, A., Guo, Y., Sera, F., Vicedo-Cabrera, A. M., Huber, V., Tong, S., Coelho, M. de S. Z. S., Saldiva, P. H. N., Lavigne, E., & Correa, P. M. (2017). Projections of temperature-related excess mortality under climate change scenarios. *The Lancet Planetary Health*, *1*(9), e360–e367.

Ghil, M. (2002). Advanced spectral methods for climatic time series. *Reviews of Geophysics*, *40*(1), 1003. https://doi.org/10.1029/2000RG000092

Glanemann, N., Willner, S. N., & Levermann, A. (2020). Paris Climate Agreement passes the cost-benefit test. *Nature Communications*, *11*(1), 110. https://doi.org/10.1038/s41467-019-13961-1

Hasselmann, K. (1976). Stochastic climate models Part I. Theory. *Tellus*, *28*(6), 473–485. https://doi.org/10.1111/j.2153-3490.1976.tb00696.x

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics*, *8*, 43–75.

Imbers, J., Lopez, A., Huntingford, C., & Allen, M. R. (2013). Testing the robustness of the anthropogenic climate change detection statements using different empirical models. *Journal of Geophysical Research: Atmospheres*, *118*(8), 3192–3199. https://doi.org/10.1002/jgrd.50296

Kalkuhl, M., & Wenz, L. (2020). The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management*, *103*, 102360. https://doi.org/10.1016/j.jeem.2020.102360

Kolstad, C. D., & Moore, F. C. (2020). Estimating the economic impacts of climate change using weather observations. *Review of Environmental Economics and Policy*, *14*(1), 1–24.

Letta, M., & Tol, R. S. J. (2019). Weather, Climate and Total Factor Productivity. *Environmental and Resource Economics*, *73*(1), 283–305. https://doi.org/10.1007/s10640-018-0262-8

Lorenz, E. N. (1963). Deterministic Nonperiodic Flow. *Journal of the Atmospheric Sciences*, *20*(2), 130–141. https://doi.org/10.1175/1520-0469(1963)020<0130:DNF>2.0.CO;2

Mann, M. E., Steinman, B. A., & Miller, S. K. (2014). On forced temperature changes, internal variability, and the AMO. *Geophysical Research Letters*, *41*(9), 3211–3219. https://doi.org/10.1002/2014GL059233

Mann, M. E., Steinman, B. A., & Miller, S. K. (2020). Absence of internal multidecadal and interdecadal oscillations in climate model simulations. *Nature Communications*, *11*(1), 49. https://doi.org/10.1038/s41467-019-13823-w

Matsuura, K., & Willmott, C. J. (2018a). Terrestrial air temperature: 1900–2017 gridded monthly time series. *University of Delaware, Newark, DE Retreived from. Http://Climate. Geog. Udel. Edu/∼Climate/Html_pages/Global2017/README. GlobalTsT2017. Html*.

Matsuura, K., & Willmott, C. J. (2018b). Terrestrial precipitation: 1900–2017 gridded monthly time series. *Electronic. Department of Geography, University of Delaware, Newark, DE*, *19716*.

Mérel, P., & Gammans, M. (2021). Climate Econometrics: Can the Panel Approach Account for Long-Run Adaptation? *American Journal of Agricultural Economics*, *n/a*(n/a), 1–32. https://doi.org/10.1111/ajae.12200

Moore, F. C., & Diaz, D. B. (2015). Temperature Impacts on Economic Growth Warrant Stringent Mitigation Policy. *Nature Climate Change*.

Moore, Frances C, & Diaz, D. B. (2015). Temperature impacts on economic growth warrant stringent mitigation policy. *Nature Climate Change*, *5*(2), 127.

Moyer, E. J., Woolley, M. D., Matteson, N. J., Glotter, M. J., & Weisbach, D. A. (2014). Climate impacts on economic growth as drivers of uncertainty in the social cost of carbon. *The Journal of Legal Studies*, *43*(2), 401–425.

Moyer, E., Woolley, M., Glotter, M., & Weisbach, D. (2014). Climate Impacts on Economic Growth as Drivers of Uncertainty in the Social Cost of Carbon. *Journal of Legal Studies*, *43*(2), 401–425.

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Newell, R. G., Prest, B. C., & Sexton, S. E. (2020). The GDP-Temperature Relationship: Implications for Climate Change Damages. *Resources for the Future*, 71.

Ricke, K., Drouet, L., Caldeira, K., & Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, *8*(10), 895.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15594–15598.

Smith, J. O. (2007). *Mathematics of the Discrete Fourier Transform (DFT): With Audio Applications*. Julius Smith.

Taraz, V. (2017). Adaptation to climate change: Historical evidence from the Indian monsoon. *Environment and Development Economics*, *22*(5), 517–545.

Tardif, R., Hakim, G. J., Perkins, W. A., Horlick, K. A., Erb, M. P., Emile-Geay, J., Anderson, D. M., Steig, E. J., & Noone, D. (2019). Last Millennium Reanalysis with an expanded proxy database and seasonal proxy modeling. *Climate of the Past*, *15*(4).

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*(4), 485–498.

World Bank. (2021). *World Bank Open Data*. https://data.worldbank.org/

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Code availability

The code to replicate the analysis and figures is in: https://github.com/BerBastien/TempEffectGDP

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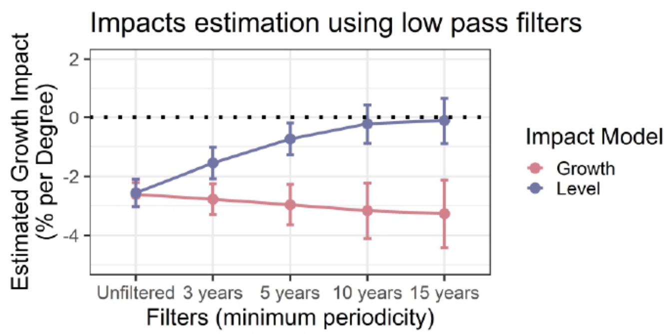
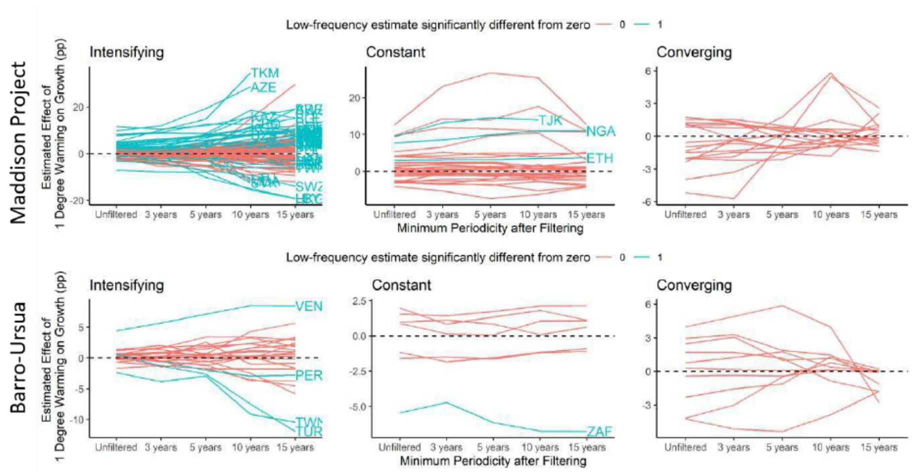
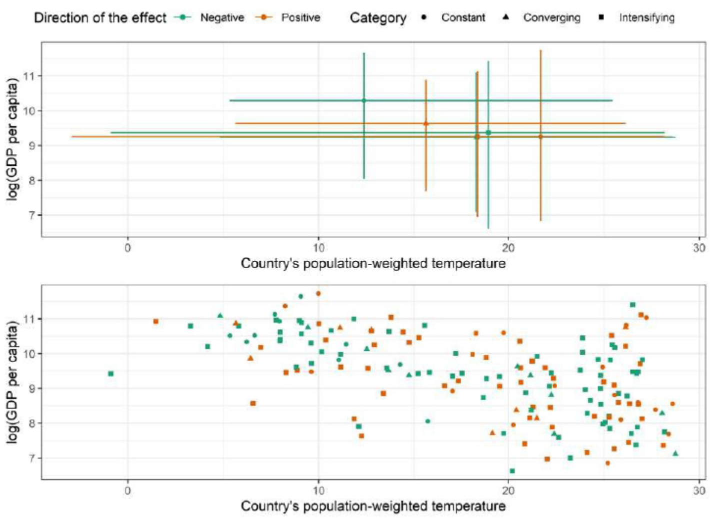
Supplementary Figures



Supplementary Figure 1. Same simulation as described for Figure 2 but adding iid noise (SD=0.01) to the temperature time series. True size effect = -5%. Note that coefficients in the levels model still trend towards zero at longer filters, but impacts in the growth model intensify slightly due to reduced attenuation bias from filtering out noise in the temperature time series.



Supplementary Figure 2. Categorization of temperature coefficient estimates for different levels of filtering using alternate economic growth datasets. Top row: Maddison Project economic dataset (Bolt & van Zanden, 2020), bottom row: Barro-Ursua project economic dataset (R. Barro & Ursua, 2010).



Supplementary Figure 3. Top: The range and mean values of country's mean temperature and log of the GDP per capita for each category of low-frequency effect estimate. Bottom: countries' category, mean temperature and logarithm of the GDP.

Conclusion

Ecosystems provide diverse benefits to people, from non-use values to market goods. However, climate change has already damaged many ecosystems, and more pronounced and widespread disturbances are expected in the future. With the research presented in this dissertation, my aim is to build a framework that integrates the current literature and findings on these topics to understand better how climate change will affect what we value from nature. In this section, I discuss the joint contribution of the papers presented above, their limitations, and priorities for future research.

Contributions and Implications

Within the long-standing and contested quest of defining the nature of geographical thought, some authors argue that a crucial characteristic of a geographer is to draw findings and theory from multiple disciplines to try to solve a current problem. While many can disagree with this broad definition, I believe this accurately encapsulates my dissertation's main contribution. By deeply analyzing state-of-the-art literature in environmental economics, sustainability, ecology, and climate change, I was able to carefully weave different threads of scientific knowledge to answer my question.

In that sense, a principal contribution of this dissertation is bringing together in a coherent framework different lines of research to shed light on how climate change will impact the benefits we obtain from nature. This is especially reflected in the Introduction of this dissertation, a review article that Dr. Frances Moore and I were invited to write for the Volume 14 of the Annual Review of Resource Economics. It is expected to serve as a map for future researchers to advance the field.

From a more specific angle, Chapter 1 contributes to representing better use and non-use values of nature in DICE, a widely used integrated assessment model of climate and the economy. The standard approach bundled market and out-of-market climate impacts in a stylized damage function that reduced a percentage of economic output equivalent to the out-of-market losses. This makes it impossible to distinguish between market and out-of-market damages, effectively allowing to compensate one-to-one the different types of losses even if they mean completely different things to society.

Only a few articles before have explicitly included an environmental amenity in the utility function as a separate component from the economic output and investigated the effects on climate policy. As Chapter 1 shows, I expanded the DICE model beyond these modifications in at least two ways. Firstly, by further disentangling the environmental amenities component into non-market ecosystem services and non-use values. While both bring benefits to society, ecosystem services only arise when ecosystems interact with people and the built environment. On the other hand, non-use values are independent of any localized interaction of ecosystems with people or manufactured capital. I integrate these two components using a nested utility function to allow different degrees of substitutability.

Secondly, building on the macroeconomic theory of capital and digging into some mostly forgotten ideas that originated as part of the heated debates on limits to growth, I extend the economic production function to account for natural capital. This is enabled by the information generated by international organizations such as the World Bank that have done constant and systematic work on wealth accounting. I call GreenDICE to this extended version of the DICE model. The optimal social cost of carbon, a widely used climate policy-relevant estimate, is five times larger in 2020 compared to the values given by the standard version of DICE. If the optimal SCC given by GreenDICE was applied globally as a carbon tax, it would limit global temperature below 2C.

In addition, an important contribution is a focus on better representing the dynamics of ecosystems within this integrated approach. Using output from terrestrial ecosystem models and ecosystem services valuation studies, Chapter 2 shows that it is feasible to attach a value to the benefits of different biomes covering each country. With that, I can estimate future changes in the market and non-market benefits due to ecosystems moving poleward and to higher altitudes in a warmer future. Additionally, this research depicts a process that further intensifies the inequality gap across countries.

Finally, Chapter 3 presents results from a distinct perspective. In an empirical exercise with an innovative methodological approach, I identified the presence of persistent -and, therefore, cumulative - temperature effects on some countries' gross domestic product (GDP). As opposed to the otherwise widely used assumption of the presence of level-only effects, which are temporary temperature damages reversed after the temperature shock passed. The scientific literature has increasingly studied the processes that would generate persistent temperature effects. Among these processes are damages to the economic productive base, such as climate change lowering natural capital as depicted in GreenDICE. An independent empirical study that detects persistent effects indicates that models such as GreenDICE should continue to be explored.

Limitations and Future Research

The studies presented here explore only one among the countless ways to approach the question of how climate change is affecting the benefits we get from nature. While the results are robust to parametric uncertainty and shed light on important implications, many assumptions remain uncontested. In this final section, I explore some of these assumptions and point to relevant research venues I plan to undertake in the future.

The benefits that nature provides to people are unique to each community worldwide. These benefits arise from the interaction of people with diverse ecosystems and are mediated by culture, institutions, and many more unique characteristics resulting from historical processes. A global model like the one I present in this dissertation is not made to integrate all these distinctive ways to experience human-nature interactions. Rather, it draws from a top-to-bottom narrative often imposed by a dominant thought framework. It is crucial to develop concerted local-specific research that provides a mosaic of local-level analysis of climate impacts on human-nature relations while allowing for the uniqueness of worldviews and value systems. These necessarily have to come from a bottom-to-top approach, and instead of being part of single research, it is a task for a whole community that is still emerging.

On a more specific note, some rough edges call for further research in the future. For instance, the concept and methods of measuring natural capital have to be better defined depending on the direction in which natural capital is measured. Traditionally, sustainability theory has measured the capital with a backward-looking approach to assessing whether the productive base of the society is on a sustainable pathway. However, natural capital as used here, in a forward-looking assessment, should take into account multiple future pathways. This is already common in the scenarios community that model socioeconomic pathways and greenhouse gas emissions. However, the concept is harder to grasp for natural capital, given the nature of its calculation, especially under uncertain climate and management practices. Different climate and policy scenarios would lead us to calculate a different estimate of natural capital today, as opposed to what we get in the emission scenarios, where future pathways do not affect current levels of greenhouse gas emissions. Much work is left in better problematizing and advancing concerted efforts of forward-looking accounts of natural capital.

Remarkably, two assumptions require further attention as they could be causing either an underestimation or overestimation of the results presented in Chapter 2. First, those results only consider biomes shifting, while there are many potential changes at other ecological levels, for example, community composition, functionality, biodiversity, primary productivity, and more. None of these is considered, which would likely intensify climate change impacts.

Further, another assumption is that countries do not adapt to their changing ecosystems. Adaptation measures can attenuate lost benefits when ecosystems shift. Not accounting for societies adapting to new ecosystems might be a source of overestimating the results and should be approached in future research.

Finally, the ecological scope has been limited to terrestrial biomes. However, many coastal communities and insular nations have deeper connections with the oceans. While much work has measured fisheries' value, ongoing efforts are emerging to recognize beyond-market benefits that oceans provide to people worldwide. This is an exciting line of research on where I will focus next.

Even in the light of the limitations mentioned above, this dissertation provides a solid contribution to the field of climate change impacts on nature and society.