Environmental and Resource Economics
https://doi.org/10.1007/s10640-025-01042-5

Global Evidence on the Income Elasticity of Willingness to Pay, Relative Price Changes and Public Natural Capital Values

Moritz A. Drupp[1,2] · **Zachary M. Turk**[3] · **Ben Groom**[4,5] · **Jonas Heckenhahn**[6]

Received: 28 April 2025 / Revised: 13 August 2025 / Accepted: 22 September 2025

Abstract

While the global economy continues to grow, ecosystem services tend to stagnate or decline. Economic theory has shown how such shifts in relative scarcities can be reflected in project appraisal and accounting, but empirical evidence has been sparse to put theory into practice. To estimate relative price changes (RPCs) for ecosystem services to be used for making such adjustments, we perform a global meta-analysis of contingent valuation studies to derive income elasticities of marginal willingness to pay (WTP) for ecosystem services to proxy the degree of limited substitutability. Based on 735 income-WTP pairs from 396 studies, we find an income elasticity of WTP of around 0.6. Combined with good-specific growth rates, we estimate an RPC of ecosystem services of around 1.7% per year. In an application to natural capital valuation of forest ecosystem services by the World Bank, we show that natural capital should be uplifted by around 40%. Our assessment of aggregate public natural capital yields a larger value adjustment of between 58 and 97%, depending on the discount rate. We discuss implications for policy appraisal and for estimates of natural capital in comprehensive wealth accounts.

Keywords Willingness to pay · Ecosystem services · Income elasticity · Limited substitutability · Growth · Relative prices · Contingent valuation · Forests · Natural capital

JEL Codes D61 · H43 · Q51 · Q54 · Q58

✉ Moritz A. Drupp
mdrupp@ethz.ch

[1] Department Management, Technology, and Economics, ETH Zurich, Zurich, Switzerland

[2] Department of Economics, University of Gothenburg, Gothenburg, Sweden

[3] Department of Socioeconomics, University of Hamburg, Hamburg, Germany

[4] Department of Economics, University of Exeter Business School, Exeter, UK

[5] Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science, London, UK

[6] Faculty of Management and Economics, Ruhr-University Bochum, Bochum, Germany

Published online: 19 November 2025

1 Introduction

Measuring economic progress towards sustainability requires addressing the limited substitutability among the various constituents of comprehensive wealth (Smulders and van Soest 2023). Potential limits to substitution imply that society must strike a balance between the two opposing paradigms of Weak and Strong Sustainability (e.g., Neumayer 2003; Hanley et al. 2015; Dasgupta 2021). Many contemporary measures of economic progress and wealth have explicitly or implicitly followed a Weak Sustainability approach. In doing so, they consider natural capital and ecosystem services as largely substitutable—sometimes even perfectly substitutable—with human-made capital stocks. In light of the continued growth of human-made capital and the stagnation or degradation of many natural capital stocks (IPBES 2019), the Weak Sustainability approach is increasingly being called into question. From a theory perspective, we should consider some degree of imperfect substitutability when estimating shadow prices, i.e. pseudo-prices that reflect the contribution of non-market goods to intertemporal welfare (e.g., Arrow et al. 2012), the 'Achilles' heel' of wealth accounting (Smulders 2012). This is relevant both for natural capital that serves as an intermediate input to various production processes and for public natural capital as a direct source of utility (see, e.g. Zhu et al. 2019; Smulders and van Soest 2023). A common constraint to implementation, however, has been a lack of sufficient empirical evidence on the degree of substitutability of ecosystem services and natural capital to inform the computation of shadow prices (e.g. Drupp 2018; Cohen et al. 2019; Rouhi Rad et al. 2021).

This paper makes a step towards closing this important empirical evidence gap by characterising the limited degree of substitutability of ecosystem services in utility via a global meta-analysis of contingent valuation (CV) studies.[1] Doing so allows changes in the relative scarcity of ecosystem services to be more appropriately valued in policy appraisal and environmental-economic accounting. The evidence is drawn from a large global meta-analysis to estimate income elasticities of marginal willingness to pay (WTP) for ecosystem services as a proxy for the limited substitutability of ecosystem services vis-a-vis market goods. Coupled with well-defined estimates of income elasticity of WTP and good-specific growth rates, we can compute the relative price changes (RPCs) of ecosystem services. We then propose an approach to deriving adjustments to natural capital accounts and calibrate this using empirical estimates for the case of non-wood forest ecosystem service values, a key application in the World Bank's *Changing Wealth of Nations (CWON)* measure and for aggregate adjustments of public natural capital values.

There are two principal approaches to account for the limited substitutability of ecosystem services within frameworks such as Cost-Benefit Analysis (CBA) and comprehensive wealth accounting. One can either apply differentiated discount rates—often a lower discount rate for non-market ecosystem services—or account for increasing relative scarcity by adjusting the valuation (accounting price) of ecosystem services throughout the horizon of the evaluation (e.g. Weikard and Zhu 2005; Hoel and Sterner 2007; Gollier 2010; Traeger 2011; Baumgärtner et al. 2015; Drupp 2018). Several studies have already shown the importance of accounting for the adverse effects of climate change on ecosystem services, biodiversity and environmental amenities (e.g. Hoel and Sterner 2007; Sterner and Persson 2008). More recently Drupp and Hänsel (2021) and Bastien-Olvera and Moore (2021)

[1] The CV method is a prominent survey-based approach for the valuation of non-market goods and resources (see, e.g., Hanemann 1994; Kling et al. 2012, for overviews).

examined how the increasing scarcity and limited substitutability of non-market ecosystem services each affect optimal climate policy through RPCs. Drupp and Hänsel (2021), for instance, estimate that limited substitutability leads to relative prices of non-market goods increasing by around 2 to 4% per year, with estimates of the social cost of carbon being 50% higher as compared to the case of perfectly substitutable goods. Accounting for RPCs of non-market goods is thus crucial for climate policy appraisal. Perhaps more importantly, RPCs need to be accounted for properly in the appraisal of projects, regulations, and policies to better account for the impact of ecosystem services on well-being. This is routinely done, for instance, for the value of travel time or of health, two other prominent non-market goods, where values are commonly assumed to increase over time in line with expected income increases. Furthermore, when using environmental-economic accounting, e.g. within the UN System of Environmental Economic Accounting-Experimental Ecosystem Accounting (SEEA-EEA) or *CWON*, valuations that account for limited substitutability are critical to the assessment of sustainability.

Practically speaking, two components are needed to estimate the trajectory of relative prices for ecosystem services: First, the elasticity of substitution between market and non-market goods; second, their respective growth rates. Previous empirical studies have estimated the elasticity of substitution indirectly using the inverse of the income elasticity of willingness to pay (WTP) from non-market valuation studies (Baumgärtner et al. 2015; Drupp 2018; Heckenhahn and Drupp 2024). Good-specific growth rates have been estimated either using historical time series data (e.g. Baumgärtner et al. 2015; Heckenhahn and Drupp 2024), and then assuming (as we will do) constant exponential growth rates, or as endogenous outcomes in global integrated climate-economy assessment models (e.g. Sterner and Persson 2008; Bastien-Olvera and Moore 2021; Drupp and Hänsel 2021). The rate of change of relative prices is then approximated by the income elasticity of WTP multiplied by the difference between the growth rates of marketed and non-marketed goods. Baumgärtner et al. (2015) were the first to estimate RPCs in this way. Yet, their study drew on an estimate of the elasticity of substitution for just one ecosystem service: global biodiversity conservation, based on a small meta-analysis of 46 CV studies by Jacobsen and Hanley (2009). Heckenhahn and Drupp (2024) provide the first country-specific evidence for Germany, which built on just 36 WTP studies. There is thus clear scope to enhance the estimation of substitutability and evolving scarcity of ecosystem services, thereby allowing a more accurate assessment of their welfare implications.

These gaps in and limitations of the empirical evidence—the absence of both a general default for generic ecosystem services as well as ecosystem service-specific estimates of income or substitution elasticities and growth rates—mean that guidelines for governmental appraisal and environmental-economic accounting only rarely address the issue of limited substitutability of non-market goods (Groom et al. 2022). Where environmental discounting or RPCs have been integrated into governmental policy guidance, they are operationalized using very coarse estimates of growth rates and elasticities (Groom and Hepburn 2017). For instance, The Netherlands consider a general default RPC of 1% per annum for ecosystem services of all kinds in their discounting guidance, following the estimate based solely on biodiversity related services from Baumgärtner et al. (2015).[2] The UK Department for Environment, Food and Rural Affairs used to reflect relative price adjustments for the health

[2] The guidance allows specific deviations from 1% if growth or substitution possibilities deviate from the default assumptions, e.g. if the ecosystem service is deemed non-substitutable.

benefits of pollution reductions by 'uplifting' the damage costs by 2% per year. The underlying assumption here is that WTP for avoiding the health consequences of pollution grows in line with predicted income (HM Treasury 2021). Indeed, health benefits in general are discounted using a discount rate that is 2% points lower in the UK for related reasons. For the environment in general, where the guidelines do reflect changing valuations over time or lower discount rates, e.g. in the Asian Development Bank and Canadian guidelines, again rather generic rules of thumb are used that do not distinguish across different ecosystem services (Groom et al. 2022). Finally, where guidelines exist for natural capital valuation, such as the World Bank's 2021 *CWON* report, they apply to a minimal basket of non-market goods and capital stocks, and do not account for changing relative prices. For instance, in the CWON forest ecosystem services are valued using a meta-regression and spatial benefit transfer by Siikamäki et al. (2015), yet maintain constant real prices over time. In short, the benefit transfer to account for spatial differences in income is not complemented by a benefit transfer to account for intertemporal income differences.[3]

From a policy perspective, not accounting for limited substitutability of ecosystem services means that ecosystem services will be seriously undervalued in public appraisal of policy or natural capital. The underlying—often implicit—assumption in such cases is that ecosystem services are perfectly substitutable with market goods. Yet, even in the unusual cases where adjustments have been made, the assumption is too generic to properly reflect sustainability and the welfare associated with different ecosystem services. For practical purposes, then, more accurate estimates are needed, ideally differentiated across ecosystem services where sizable heterogeneities exist.

Against this background, we provide a first systematic, global empirical evidence basis to inform relative price adjustments of ecosystem services—both for a proxy of aggregate ecosystem services as well as for ecosystem services' sub-categories—thereby advancing prior work by Baumgärtner et al. (2015) and Heckenhahn and Drupp (2024).[4] These estimates can be applied to public appraisal of public investment and regulatory change, as in Drupp et al. (2024a), as well as to natural capital valuation, such as the *CWON* program and the SEEA-EEA, which we consider here. Our main focus is on improving the estimation of limited substitutability of non-market ecosystem services vis-a-vis market goods. To this end, we perform a meta-analysis of environmental values derived using the CV method to estimating the income elasticity of WTP—a key parameter also for benefit transfer across space (Baumgärtner et al. 2017a; Smith 2023). Our meta-analysis draws on a large-scale keyword-based search strategy and an in-depth analysis of more than 2000 peer-reviewed CV studies. Our full sample includes 735 mean income and WTP estimates, including recurring covariates, sourced from 396 peer-reviewed CV studies.

Our central estimate suggests an income elasticity of WTP for ecosystem services on aggregate of about 0.6, with a 95% confidence interval extending from around 0.5 to 0.7. Point estimates for different ecosystem service types range between about 0.4 (water purification and waste treatment) and 0.9 (spiritual and religious values). Using estimates of

[3] The assumption is that per-hectare monetary values are constant over time (correcting for inflation). Note, Siikamäki et al. (2015) find positive and large GDP elasticities of WTP.

[4] Our contribution relative to the recent study by Heckenhahn and Drupp (2024) is twofold: First, we provide global-level evidence on income elasticities, growth rates and RPCs based on a much larger meta-analysis that allows us to focus on a single valuation method. Second, we analyze how changes in relative scarcity affect the valuation of public natural capital values, with a focus on public forest natural capital.

good-specific growth rates, we compute RPCs of ecosystem services of around 1.7% per year on aggregate. RPCs are smaller for forest ecosystem services (1.3%), primarily due to a lower rate of de-growth of forest area. These estimates can be employed to adjust WTP estimates for project appraisal or environmental-economic accounting. In an application on natural capital valuation, taking the *CWON* 2021 report by the World Bank (2021), we show that adjusting natural capital estimates for non-timber ecosystem services for RPCs results in uplifting the present value over a 100-year time period by 40% (95 CI: 20 to 65%), materially elevating the role of public natural capital. Our estimates for adjustments to the value of aggregate public natural capital are more substantial, amounting to between 58 and 97% for our main estimate, depending on the social discount rate. These results echo work on the importance of limited substitutability in climate policy appraisal (Sterner and Persson 2008; Bastien-Olvera and Moore 2021; Drupp and Hänsel 2021). We close by discussing limitations of our analysis and by summarizing insights for project appraisal, accounting, and sustainability more generally.

2 Theoretical Background

To provide the theoretical background for our empirical analysis, we briefly sketch the workhorse model used to study RPCs in the prior literature (e.g., Weikard and Zhu 2005; Traeger 2011; Baumgärtner et al. 2015) and consider a simple case in which intertemporal well-being, determined by a standard time-discounted Utilitarian social welfare function, is derived from both human-made goods, C_t and non-market environmental goods or ecosystem services, E_t. In the general case of imperfect substitutability, ecosystem services feature explicitly in the instantaneous utility function representing preferences over market-traded consumption goods and non-market goods, $U(C_t, E_t)$. The theory of dual discounting or RPCs has shown that there are two approaches to addressing the intertemporal appraisal of non-market goods (e.g., Weikard and Zhu 2005; Gollier 2010; Traeger 2011; Baumgärtner et al. 2015):

1. Explicitly consider how the relative price of non-market goods vis-a-vis market goods changes over time. Then, compute comprehensive consumption equivalents at each point in time and use a single consumption discount rate on future comprehensive consumption equivalents.
2. Use differentiated, good-specific consumption discount rates, i.e. one for market goods, r_C, and another for non-market goods, r_E.

In the first approach, followed here, we compute the value of non-market goods in terms of the market good numeraire. This value is given by the marginal rate of substitution (MRS), U_{E_t}/U_{C_t}, which is the implicit (shadow) price of non-market goods. The RPC_t measures the change in the MRS between non-market and market goods over time, i.e. the relative change in the valuation of non-market goods (Hoel and Sterner 2007):

$$RPC_t = \frac{d}{dt}\left(\frac{U_{E_t}}{U_{C_t}}\right) / \left(\frac{U_{E_t}}{U_{C_t}}\right). \tag{1}$$

Future expected non-market values can then be adjusted using the RPC_t and a single SDR can then be used to discount future flows of private and non-market consumption.

To make this concrete and applicable, let us consider the workhorse constant-elasticity-of-substitution (CES) utility function, capturing various degrees of substitutability:

$$U(C_t, E_t) = \left(\alpha C_t^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\, E_t^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} , \tag{2}$$

$0 < \sigma < +\infty$, is the constant elasticity of substitution between the two goods, and $0 < \alpha < 1$ is the utility share parameter for private consumption. The utility function given by Eq. 2 is strictly concave, represents homothetic preferences, and both the private good, C_t, and non-market good, E_t, are normal. It turns out that with CES preferences and imperfect complements, i.e. $\sigma > 0$, we get the following straightforward equivalence between the dual discounting and RPC approaches (Weikard and Zhu 2005):

$$RPC_t, = \frac{1}{\sigma}\left[g_{C_t} - g_{E_t}\right] = r_{C_t} - r_{E_t}. \tag{3}$$

Accordingly, the choice of whether one adjusts the numerator via a relative price effect adjustment or the denominator via the use of dual discount rates is not of theoretical importance. In the setting of CES preferences, Ebert (2003) has shown that the constant elasticity of substitution between a market good and a non-market good is directly and inversely related to the income elasticity of WTP, ξ, of the non-market good (cf. Baumgärtner et al. 2017a). We can thus write the RPC as:

$$RPC_t = \xi\,\left[g_{C_t} - g_{E_t}\right], \tag{4}$$

which serves as the key equation our empirical analysis seeks to calibrate.

We then use estimated RPCs in an application to environmental-economic accounting in Sect. 5. To this end, we adjust future WTPs, along forecasted RPCs, and public natural capital values (the subsequent formulas follow the online appendix of Drupp et al. 2024a). Specifically, WTP_t grows over time at the rate RPC_t:

$$WTP_t = WTP_0 e^{RPC_t}\,. \tag{5}$$

Taking into account that the total value of a unit of ecosystem service must reflect the present value (PV) total future benefits, and using a standard (exponential) discounting applied at a (social) discount rate r over a time horizon T, the value of public natural capital is given by the PV of future ecosystem service flows, valued at time-specific WTPs:

$$PV = \int_0^T WTP_t\, e^{-rt} dt = WTP_0\, \frac{1 - e^{-(r-RPC)T}}{r - RPC}. \tag{6}$$

In a final step, we compute how the value of public natural capital (Eq. 6 increases due to RPCs, i.e. relative to the case when no relative price adjustment is performed ($PV_{noRPC} = (1 - e^{-rT})/r$):

$$\left(\frac{1-e^{-(r-RPC)T}}{r-RPC}\right)\left(\frac{1-e^{-rT}}{r}\right)^{-1}-1, \tag{7}$$

from which we will illustrate how the increase in the PV of natural capital varies across alternative estimates and assumptions concerning income elasticities, growth rates for different types of ES and discount rates.

3 Empirical Strategy

We build on previous work to estimate income elasticities of WTP for ecosystem services based non-market valuation studies (e.g., Jacobsen and Hanley 2009; Richardson and Loomis 2009; Barrio and Loureiro 2010; Subroy et al. 2019; Heckenhahn and Drupp 2024). Our meta-analysis collects mean WTP and mean income estimates at the valuation exercise level. These data are then used to estimate income elasticities of WTP and their inverse in the CES case, the elasticity of substitution between ecosystem services and market goods (cf. Ebert 2003; Baumgärtner et al. 2015; Heckenhahn and Drupp 2024). In this section, we first introduce the meta-analysis approach that casts a deliberately wide net to be able to estimate elasticities ξ for more aggregated definitions of ecosystem services as well as sub-categories.[5] Subsequently, we also estimate ecosystem service growth rates.

3.1 Meta-analysis of Mean WTP-income Value Pairs

The data basis for our analysis is a meta-analysis of existing WTP studies. The main process of dataset creation ran from May 2022 to April 2023, with additional revisions in September and October 2024.[6] In the first phase, we identified potentially relevant non-market valuation studies through a keyword-based search string provided in Appendix A.2 in the database SCOPUS. In particular, here, we built on the authors' experience (e.g., Drupp et al. 2020; Heckenhahn and Drupp 2024; Moore et al. 2024), and beta testing. To ensure better comparability of ecosystem service valuation estimates, we focused our search on CV studies that were published in peer-reviewed, English-language literature since the year 2000. The keyword-based search resulted in a preliminary data set where each row is a peer-reviewed journal article in which we expect to find relevant (mean) WTP estimates and income data. Generally, the employed search string was intended to cast a wide net. That is, we expected to later drop several studies due to irrelevance and informational shortcomings.

The data was then evaluated using the exclusion criteria reported in Appendix A.3. After the application of the first exclusion criterion—including whether each article has been cited at least once in SCOPUS—2,174 articles remained. The next exclusion criteria step is an abstract screening to check whether the articles potentially report new, CV-based WTP estimates at all. Strictly theoretical papers as well as reviews, secondary source estimates, and those focused on benefit transfer were excluded to avoid double-counting estimates. Naturally, whether we could access the articles was important but rarely proved to be an

[5] Appendix E provides details on how our meta-analysis follows best-practice recommendations provided by Stanley and Doucouliagos (2012).

[6] Figure 4 in Appendix A.1 shows a PRISMA flow diagram with study identification and screening steps.

issue. At this stage, 1,165 studies remained on which to conduct a detailed screening and subsequent data harvesting.

From the data set of 1,165 WTP studies, we selected a random sample of 100 studies as the basis to fine-tune the screening and coding processes and improve consistency between our two independent coders, we then proceeded to code the full sample. Each paper was carefully scrutinized for appropriate WTP and income data (see Appendix A.3 for details). A recurring issue was that several papers do not report whether income data is net of taxes or gross income. We have subsequently contacted each paper's corresponding author in search of clarification, with a response rate of around 40%.[7] The review of each paper and harvesting of relevant data was a particularly time-intensive process. However, we found it easier to first screen for the inclusion of both mean WTP and mean income estimates—or the information necessary to derive such estimates—before harvesting all relevant data. We also found that there is an important distinction on per-use estimates versus other scales. When per-use estimates have not been paired with the number of uses on a per-respondent scale, they are not comparable—we do not know whether respondents with higher or lower willingness to pay also access the service more or less. As such, per use estimates are set aside.

Finally, 16 studies (with 69 estimates) report different scales of ecosystem services, say a 10-percent versus 25-percent versus 50-percent level of provision. When this is the case, we take the most marginal estimate—the smallest change from current conditions—as this corresponds to valuing the level of ecosystem service most similar to the current state, i.e. the closest to the respondents' lived experience.

Our main analysis builds on studies surviving our exclusion criteria and containing at least the minimum necessary information—a mean WTP estimate and mean respondent income estimate. An unfortunate but necessary result of our focus on comparability is a substantially reduced number of studies contributing to the end result. Of the 1,165 studies passing the first two rounds of screening, 396 studies containing 735 distinct WTP-income pairs are of use. Table 1 provides summary statistics of our sample. Appendix B includes graphical illustrations of the meta-analysis data. Appendix G, available in the online Supplementary information, provides the full list of included studies and their respective references.

Further, Table 2 presents the number of WTP estimates associated with the regulating and cultural ecosystem services, as introduced in the Millennium Ecosystem Assessment (MEA 2005)[8], along with estimates related to biodiversity and forest services. Also, for each service type, an example study from our dataset is provided.

Note that as WTP estimates are often associated with more than one service type, the total number of observations for different ecosystem service types exceeds 735, with observations roughly evenly distributed between regulating and cultural services.[9] In our analysis, we control for the number of ecosystem services a WTP estimate relates to.

Beyond that, our inclusive approach to collecting WTP estimates (see Appendix A.2), characterized by an open definition of ecosystem services to maximize sample size, allows for considerable heterogeneity in the specific valuation object, which remains when focus-

[7] If no answer was received, we coded the net-gross dummy as "unclear".

[8] Note that while we linked WTP estimates to all distinct regulating service types presented within the MEA (2005) framework, we focused on only two cultural service types, thereby excluding services like sense of place, laid out in the framework, as well.

[9] For our dataset, WTP estimate overlapping is particularly common between climate and air quality regulation, as well as between aesthetic values and recreation & ecotourism.

Table 1 Prepared data set description

Variable	Context	Value
Countries represented	Count	74
Continent	Observations	
North America		88
South America		37
Africa		35
Europe		269
Asia		300
Australia		6
Study year	Mean (s.d.)	2009 (6.5)
Income	Mean annual, 2020 USD (s.d.)	38,092 (27,297)
WTP	Mean annual, 2020 USD (s.d.)	164 (532)
Survey sample size	Mean (s.d.)	665 (851)
Respondent age	Mean (s.d.)	43 (6.6)
Respondent household size	Mean (s.d.)	3.7 (1.3)
Forest-relevant estimates	Share of observations	0.24

Notes: s.d. is the standard deviation of the data referenced. Based on N = 735 WTP-income pairs contained in 396 unique studies

ing on particular service types. In particular, many WTP estimates do not directly refer to the specified ecosystem service as defined but rather to related aspects or proxies. Climate regulation studies, for instance, are frequently related to forest conservation efforts, like the Table example study of Tolunay and Başsüllü (2015). However, they also include studies focusing on general carbon emission reduction (e.g., Yang et al. 2014), or, more specifically, on renewable energy provision (e.g., Dogan and Muhammad 2019). While air quality regulation WTP estimates are often linked to forest conservation as well (e.g., Schläpfer and Getzner 2020), they frequently focus on direct air quality enhancements as in Guo et al. (2020). The downside of our inclusive approach is reduced 'commodity consistency' (e.g., Bergstrom and Taylor 2006; Moeltner and Rosenberger 2014) as compared to meta-analyses that focus on very specific ecosystem services. We do not regard this as a limitation but as a key purpose of our analysis, as we seek to obtain an aggregate measure of the elasticity across all ecosystem services to be used as a proxy for performing RPC adjustments to WTP estimates in aggregate settings. In addition to generating a proxy for a coarse aggregate ecosystem service good, this also allows us to explore heterogeneities across key ecosystem service sub-types.

3.2 Estimation Strategy

Due to the nature of our meta-analysis, which combines data from studies using slightly differing methodologies in the common domain of contingent valuation, estimating the income elasticity of WTP requires careful consideration. To closely match and calibrate the theoretical framework, we use a log-log specification on mean WTP and mean income values, to directly capture a constant income elasticity of WTP. As we show below, this also provides a substantially better fit for our data as compared to common alternatives (e.g., semi-log, quadratic etc.). We account for the structure of our data by clustering standard errors at the study level.

Table 2 Ecosystem service categories

Category	Description	N	Example study
Regulating services			
Water regulation	Land cover changes influence runoff, flooding, and aquifer recharge.	212	Bliem and Getzner (2012)
Air quality regulation	Releasing and absorbing chemicals from the atmosphere.	186	Guo et al. (2020)
Climate regulation	Local: Land cover affects temperature and precipitation; global: Sequestration or emission of greenhouse gases.	165	Tolunay and Başsüllü (2015)
Erosion regulation	Vegetative cover is vital for soil retention and landslide prevention.	125	Huenchuleo et al. (2012)
Water purification & waste treatment	Ecosystems can be sources of impurities but filter and decompose organic waste and assimilate and detoxify compounds.	95	Tziakis et al. (2009)
Natural hazard regulation	Coastal ecosystems (e.g., mangroves) reduce hurricane and wave damages.	72	Petrolia and Kim (2009)
Disease regulation	Ecosystems alter abundance of human pathogens (e.g., cholera) and disease vectors (e.g., mosquitos).	32	Adams et al. (2020)
Pest regulation	Ecosystems influence the prevalence of crop and livestock pests and diseases.	6	Adams et al. (2020)
Pollination	Ecosystems influence the distribution, abundance, and effectiveness of pollinators.	3	Mwebaze et al. (2018)
Cultural services			
Aesthetic values	People enjoy nature's beauty, for instance, in parks and scenic drives.	341	Maharana et al. (2000)
Recreation & ecotourism	People chose leisure activities based on natural or cultivated landscape traits.	338	Ma et al. (2021)
Spiritual & religious values	Religions attribute spiritual significance to ecosystems or their components.	57	Endalew et al. (2020)
Additional sub-types			
Biodiversity	Supports ecosystem resilience, productivity, and key functions, enabling regulating and cultural services.	343	Meyerhoff et al. (2012)
Forest services (non-market)	Provide regulating services, such as climate and air quality regulation, and cultural services.	177	Al-Assaf (2015)

Notes: Description of ecosystem services types are taken from the Millennium Ecosystem Assessment (MEA, 2005) and were adapted for the table

Several covariates, which may have a direct effect on WTP, would also affect the estimated coefficient of interest if omitted.[10] We categorize potential covariates as those related to survey characteristics, income and WTP measures, or ecosystem service. First, survey characteristics include the survey year, the sample size, the method of elicitation (dichotomous choice, open-ended, or other formats), the format used to collect the study data (written questionnaires, oral interviews, or a mix), and a payment vehicle indicator (tax, donation, use charge, free choice, or a mix) which was previously used by Jacobsen and Hanley (2009). In addition, we include indicator variables on observations from countries representing 5% or more of our dataset—which applies to four countries. Second, income

[10] While we include a comprehensive set of covariates to adjust for potential confounding factors, we do not assign weights or formally evaluate the relative importance of individual covariates. Some may have stronger effects than others, but our focus is not on their standalone contributions.

and WTP characteristics reflect whether income is reported as gross or net, per-person or per-household, and the WTP payment terms (whether reoccurring or one-time). Third, ecosystem service characteristics include the types associated with the respondent's WTP categorized as in the Millennium Ecosystem Assessment (MEA 2005) and outlined in Table 2 (e.g., climate regulation). This group also includes indicators on the scope of ecosystem services (i.e., the number of services the WTP estimate pertains to) and the spatial scale of the program, project, or policy (local/regional, national, or international) to which the WTP value is linked. Our main model specification is then:

$$ln(WTP_{ij}) = \alpha + \xi\, ln(INC_{ij}) + \sum_{k=1}^{n} \beta_k x_{ij} + \epsilon_i \qquad (8)$$

where $\sum_{k=1}^{n} \beta_k x_{ij}$ indicates the inclusion of our list of n preferred covariates.

As a sensitivity analysis, we also include covariates on respondent age, household size, survey format (written, oral, hybrid), continent, period (pre- versus post-2011) and whether the ecosystem service involved forests. Age and household size, in particular, are less often available and so would reduce sample size while not being particularly relevant. We estimate a large set of alternative models—based on variations of our covariates, resulting in $2^{15} = 32,768$ versions around our main log-log specification (see Fig. 6 in the Appendix). These alternatives are based on either including or excluding each covariate in different combinations but keeping the list of ecosystem services indicator variables together—either including or excluding them as a group to avoid estimating a substantially larger set of alternatives. Study sample size varies substantially, with a mean of 665 and a standard deviation of 851. Our preferred weighting approach uses the square-root of sample size at the WTP estimate scale. This implies that we put weight on sample size while ensuring that the results are not disproportionately driven by a few large studies.[11]

We use a random effects model to capture both within- and between-variance as the source of estimates, following prior work by Jacobsen and Hanley (2009) and Heckenhahn and Drupp (2024).[12] This choice is supported by a Hausman Specification Test contrasting fixed and random effects models (while excluding any singleton studies). So, we proceed with a random effects, multivariate model with the square root of sample size weights as our main specification.[13]

We present alternative model specifications, including univariate and multivariate random and fixed effects, multi-level random-effects, OLS, unweighted, and alternative weighted models (e.g., inverse square root of sample size (cf. Subroy et al. 2019) in the

[11] We compare alternative estimators and observation weights in Figs. 7 and 8 in the Appendix

[12] Ideally, we would have multiple similar observations at the country or study level and could rely on a fixed effects model to control for the omission of invariant factors. However, studies often have specific geographic focuses within countries, in other cases involve international issues, and in yet other cases involve less comparable groups (e.g., urban versus rural, visitors versus locals) and so study- and country-level fixed effects would not, in fact, work as intended. Additionally, 272 of 396 studies (69%) and 735 estimates (37% of the dataset) are single observation studies – or singletons. These provide no within-variance and so are in effect dropped during fixed effect model estimation.

[13] Based on this model, we also conduct Ramsey's Regression Specification Error Test to compare different specifications and obtain the following results: Log–log model: $\chi^2 = 352.43$ ($p = 0.000$), linear model: $\chi^2 = 39.96$ ($p = 0.472$), quadratic model: $\chi^2 = 41.27$ ($p = 0.459$), semi-log model: $\chi^2 = 40.74$ ($p = 0.438$). These results clearly indicate that the log–log specification provides the best fit for our data.

Appendix. Separately, we explore heterogeneity in income elasticities. First, we compare differences across ecosystem service types. Second, we test how income elasticities differ across continents. Third, we test for differences across periods (pre- and post-2011). Fourth, we test for differences based on whether we include the most marginal, average, or all estimates with different levels of service provision. Finally, we explore whether estimates differ in income by comparing different segments of the income distribution.

3.3 Growth Rates

We assemble growth rates of ecosystem services to obtain a rough proxy for a global measure of the shift in the relative scarcity of ecosystem services vis-a-vis human-made goods. These estimates extend and update prior work by Baumgärtner et al. (2015), who found that ecosystem services have overall declined by half a percent in the last decades. We focus on non-market (and non-rivalrous) ecosystem services, i.e. we do not consider provisioning services but solely capture regulating and cultural services. In a first step, we update the data sources employed by Baumgärtner et al. (2015), notably: Forest cover, Living Planet Index (LPI), and IUCNs Red List Index (RLI). We complement this with two additional measures for regulating services that capture highly salient aspects of environmental quality: air quality regulation and climate regulation. We proxy the former by the negative of changes in PM2.5 emissions, i.e. counting reductions in emission as an improvement in air quality. We proxy for the latter with the change in the 2C global mean temperature budget—the upper target of the UN Paris Agreement. Table 3 shows the individual components, units of measurement, and data sources.

Within regulating (forest, LPI, RLI, PM2.5, temperature) and cultural services (forest, LPI, RLI) as well as aggregate ecosystem services, we take the arithmetic mean of individual components. To calculate growth rates, we use the time span with the longest comparable data (1993 to 2016) and estimate exponential growth rates, including standard errors. We use the largest standard error of the individual growth rate components—climate for regulating and aggregate services, and the living planet index for cultural services—when aggregating standard errors. Akin to estimating growth rates of ecosystem services, we also estimate the growth rate of global GDP per capita and its standard error. In contrast to

Table 3 Components and data sources for estimates of growth rates

Component	Unit of measurement	Data source
Forest area	Hectare	WorldBank (2023)
Living Planet Index (LPI)	Dimensionless	Zoological Society of London, and WWF 2022
Red List Index (RLI)	Various	IUCN RedList (2023), based on Butchart et al. (2010)
Air quality (mean annual PM2.5)	Micrograms per m^3	WorldBank (2023)
Climate regulation	Degrees Celsius	NOAA (2023)
GDP per capita	US dollars	WorldBank (2023)

Baumgärtner et al. (2015), we do not subtract provisioning services, as we do not examine it as a separate ecosystem service category.[14]

4 Results

We now present our estimates of income elasticities of WTP, ξ, for ecosystem services globally as well as select regions. We also estimate income elasticities based on subcategories of ecosystem services as well as different time frames. We subsequently couple the estimates of income elasticities with estimates of good-specific growth rates to compute RPCs of ecosystem services.

4.1 Income Elasticity of WTP for Ecosystem Services

We first estimate the income elasticity of WTP for aggregate ecosystem services based on our full sample and using key controls. Our central estimate of the income elasticity of WTP amounts to 0.59 (95-CI: 0.45 to 0.72) based on a random effects model, see Table 4.[15] Estimating via the multi-level random-effects (MLRE) model – allowing both the intercept and the slope on log income to vary across studies Stanley and Doucouliagos (2012) – yields a similar average income elasticity of WTP estimate: 0.57 (95-CI: 0.45 to 0.69).[16] We also develop a specification graph to investigate the sensitivity of our estimate to various combinations of control variables which we report in Fig. 6 of Appendix D. Compared to alternative specifications, our main estimate falls at the 63rd percentile. Our main estimate maps into a mean value for the elasticity of substitution between ecosystem services and market goods of 1.70 (95-CI: 1.38 to 2.22), indicating that ecosystem services and market goods are substitutes.

Estimates on subsets allow us to investigate the extent of heterogeneities. We consider different sub-types of ecosystem services and potential differences across continents, time

Table 4 Income elasticity of WTP for aggregate ecosystem services

ln(INCOME)	S.E.	N	Overall R^2
0.59***	0.07	735	0.28

Notes: Multivariate regressions based on Eq. 8. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

[14] All time series show a clear trend except for air quality, which deteriorates from 1990 to 2010 and improves again thereafter. We thus also redo the analysis of growth rates for the time frame 2010 to 2016.

[15] By contrast, a quasi-univariate regression—we still include indicator variables for observations from countries representing 5% or more of the data—yields an estimate of the income elasticity of WTP for ecosystem services of 0.38 (95-CI: 0.25 to 0.51). Instead of taking the most-marginal estimates when multiple levels of an ecosystem service are described, we could estimate on the average across all levels or treat each level-estimate separately (this applies to 16 studies with 69 total estimates). Estimating instead on the average in these cases results in a nearly identical estimate. If instead we include all individual estimates in these cases, the number of observations rises to 851 and the coefficient estimate on the income elasticity of WTP increases to 0.64. We note that the inclusion of a single negative WTP estimate changes the main income elasticity of WTP estimate from 0.61 to 0.59.

[16] Relaxing the RE assumption of a constant income elasticity potentially provides a better representation of cross-study heterogeneity. However, analysis of sources of variance in the MLRE model reveals that the RE model was a robust representation as slope variation accounts for just over 2% of total variance while variation in the baseline (intercept) contributes little.

frames, and income levels.[17] Table 5 reports income elasticities of WTP across different sub-types of ecosystem services: regulating and cultural services as well as key sub-categories. Generally, we find little variation in income elasticities, noting that oftentimes projects valued in CV studies encompass contributions to multiple services. We also split the sample into forest and non-forest ecosystem services, as this serves as a key input to our application on natural capital accounting in the *CWON* example in Sect. 5. We find that the income elasticity of forest ecosystem services is slightly higher than the aggregate estimate, but far from significantly so. For comparison, we present the univariate analysis alongside key subgroups in Fig. 1.

We next divide our sample by the continent on which the CV study has been undertaken, and report the results in Table 6. We note that the estimates are mostly concentrated in Asia, followed by Europe, with substantially fewer estimates from other regions.[18] In terms of income elasticities, we receive insignificant results for North and South America, while

Table 5 Heterogeneityof income elasticities of WTP across ecosystem service types

	ln(INCOME)	S.E.	N	Overall R^2
Regulating Services	0.60***	0.07	445	0.40
Water regulation	0.51***	0.13	212	0.59
Air quality regulation	0.52***	0.17	186	0.44
Climate regulation	0.76***	0.09	165	0.63
Erosion regulation	0.84***	0.12	125	0.74
Water purification & waste treatment	0.43**	0.20	95	0.48
Natural hazard regulation	0.52***	0.19	72	0.84
Cultural Services	0.65***	0.09	433	0.45
Aesthetic values	0.63***	0.08	341	0.47
Recreation & ecotourism	0.74***	0.09	338	0.51
Spiritual & religious values	0.87***	0.19	57	-
Additional sub-types				
Biodiversity	0.77***	0.09	343	0.61
Forest ecosystem services	0.66***	0.14	177	0.69

Notes: Multivariate regressions. Too few observations to compute R-squared in one case using the selected regression model. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

[17] This paper, illustrating effects in the context of the *CWON* approach, assumes constant per-hectare values for ecosystem services as a starting point, i.e., that the value per hectare does not change over time. As such, our model does not include estimates of the effect on value of an area shifting from, say, a tropical forest towards becoming an arid savannah. Since stated preference studies typically estimate WTP at a specific site and time, most do not provide information on how per-hectare values would evolve with ecological changes. Indeed, both the dynamics of incomes and the ecosystem in question are often not made very explicit in the primary valuation exercises. In contrast, recent work by Bastien-Olvera et al. (2024) explicitly model the ecological and economic effects of climate-induced shifts in vegetation using a dynamic global vegetation model, which presents a depiction of how both ecosystem extent and per-hectare values change over time. Their approach captures another important dimension driving changing ecosystem service values. Our results do imply some changing income elasticities of WTP over time but we cannot causally pin this down or link this to per-hectare value changes, as differences across studies over time may reflect changes in other characteristics. We do also test for differences in the income elasticity of WTP between tropical and nontropical forest-focussed studies in Appendix F, finding insufficient evidence of a difference. Yet differences in rates of change between different land uses will still result in different RPC estimates even for a common elasticity estimate. We relax the assumption of constant per-hectare values in Sect. 5, where we adjust future WTPs in line with forecasts RPCs.

[18] Several studies from Africa involve day trips and other per-use scenarios and are excluded here.

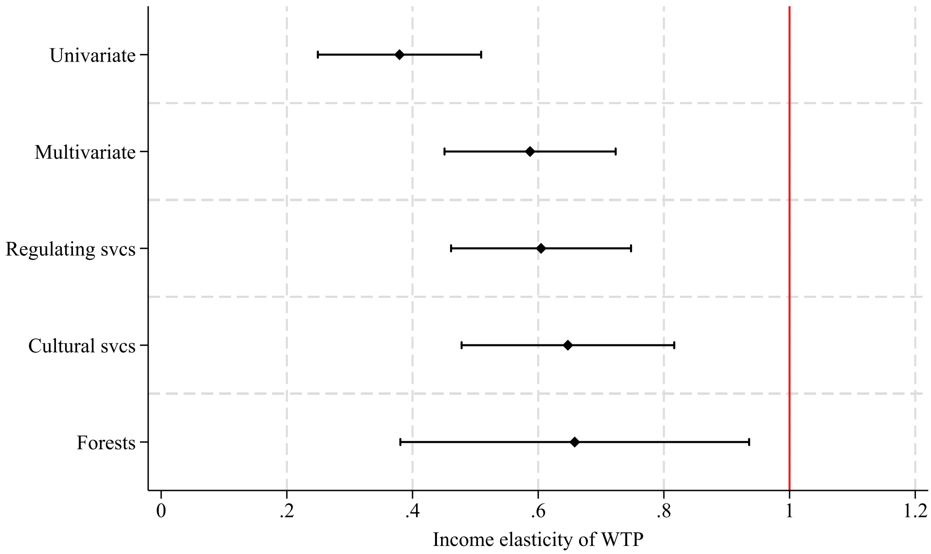

Fig. 1 Estimates of the income elasticity of WTP for select models and service types. *Notes:* Estimates are the coefficients on $ln(INCOME)$ from the main and univariate specifications in Table 5 as well as estimates based on subsets of observations on regulating services, and cultural services, and forests using the main model. 95% confidence interval estimates are included around the point estimates

Table 6 Heterogeneity of income elasticities of WTP across continents

	ln(INCOME)	S.E.	N	Overall R^2
North America	0.86	0.72	88	0.71
South America	−0.07	0.62	37	-
Africa	0.80***	0.17	38	-
Europe	0.82***	0.13	269	0.56
Asia	0.28***	0.11	300	0.51

Notes: Multivariate regressions. Too few studies in South America and Africa with multiple estimates to base an overall R-squared value on with the selected regression model (insufficient within variance). Significance levels: * p<0.1, ** p<0.05, *** p<0.01

values in Europe and Africa are larger than our main estimate, and Asia's estimate is clearly below. This is broadly in line with findings from the recent literature (Bastien-Olvera et al. 2024; Conte et al. 2025), which has emphasized the role of regional and contextual factors –such as environmental endowments and substitutability—in shaping the valuation of non-market environmental goods.[19]

The largest prior comparable meta-analysis on the income elasticity of WTP (for biodiversity conservation only) was conducted by Jacobsen and Hanley (2009). Their main result was an income elasticity of WTP estimate of 0.38, but published 16 years ago. It is, thus, interesting to investigate how our estimate of the income elasticity of WTP relates in a more

[19] Estimating the income elasticity of WTP via the MLRE model (e.g., Conte et al. 2025), where the slope and intercept are allowed to differ at the continent level, reveals modest differences in baseline WTP (intercepts), but not in the variation in how income affects WTP (slopes). Yet, the overall picture is approximately the same as our main estimate: 0.52 (95-CI: 0.39 to 0.66)

Table 7 Heterogeneity of income elasticities of WTP across decades

	ln(INCOME)	S.E.	N	Overall R^2
pre-2011	0.65***	0.11	400	0.29
2011-2021	0.55***	0.09	335	0.56

Notes: Multivariate regression-based. Excludes studies where the year of data collection is uncertain and the study authors could not be contacted for clarification. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

Table 8 Income elasticity of WTP for ecosystem services across income brackets

Sample	ln(INCOME)	S.E.	N	Overall R^2
Below median	0.68***	0.07	367	0.35
Above median	0.71***	0.21	368	0.52
Bottom 25%	0.67***	0.12	183	0.34
Top 25%	1.91***	0.54	183	0.67

Notes: Multivariate regressions. The set of controls including the study year, sample size, income information (gross/net, individual/household), payment type and elicitation method. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

comparable time frame and in comparison to the most recent decade. In Table 7 we break down the sample by sampling year. We conduct this analysis based on our multivariate estimation strategy. First, we consider estimates from publications based on samples collected up to and including the year 2010 and find an income elasticity of 0.65 in our full model with controls. In contrast, the income elasticity for 2011 onwards is slightly lower, at 0.55 (see Table 7).[20] Thus, overall, the evidence regarding elasticity changes over time seems mixed: while based on our data, we find larger elasticity values than Jacobsen and Hanley (2009), the income elasticity is lower for the later period within our split sample analysis. Two other differences in the meta-analysis by Jacobsen and Hanley (2009) and ours concern the ecosystem service type under consideration (biodiversity in their case) and whether grey literature was also included in the analysis. On the first, we do not find evidence that income elasticities are different for biodiversity-related CV studies (see Table 4). On the latter, Heckenhahn and Drupp (2024) find a larger income elasticity estimate when focusing on peer-reviewed literature only in their German case study.

Finally, we examine whether income elasticity estimates differ across income levels (see Table 8). Previous work by Barbier et al. (2017) and Ready et al. (2002) had suggested that estimates of income elasticities might increase along income levels by examining data in primary CV studies. Here, we now examine how estimates of income elasticities differ across income levels in our aggregate-level data set.[21] To this end, we first consider a

[20] Naturally, we here cannot provide a clean test of changes in the elasticity over time, as many aspects of studies in the pre-2011 and post time frames will be different. On the one hand, study protocols and methods have improved over time, on the other hand, changing macro-trends (e.g., a further decline in threatened species (e.g., Conte et al. 2025) may affect the foci of valuation studies. Our time split here is thus exploratory, as we have limited control of potential drivers.

[21] Note there could be differences in the types of ecosystem services valued across high- and low-income countries that could introduce omitted variables bias in our meta-regression analyses. For instance, regarding fishing activities, in high-income countries, WTP might rather be associated with the recreational domain, while in low-income countries, even though we generally exclude WTP explicitly focusing on provisioning services, people may tend to perceive fishing as more of a means of subsistence.

median split and find comparable estimates when groups as below versus above (inclusive) median income.

We explored further ways of cutting the data, using thirds, quartiles and quintiles as well. For instance, when comparing the bottom with the top quartiles, we find a substantially larger income elasticity of WTP for the top 25% income group. Overall, we thus find some evidence that the income elasticity of WTP may increase along income levels. That income elasticity estimate may increase with income or seem to be higher in high-income settings echoes recent findings in the literature (see, e.g., Barbier et al. 2017; Heckenhahn and Drupp 2024).

4.2 Growth Rates

Table 9 reports estimates on the growth rates of ecosystem service categories and their standard errors, alongside the growth rate of GDP per capita. Growth metrics are estimated based on data for the longest common time frame, for the years 1993 to 2016.

We find substantial heterogeneity in growth rates. The LPI and climate regulation metrics show the largest negative rates, while the change in forest area and air quality metrics show the lowest rates of change.[22] Our estimate of aggregate ecosystem service change is −1.01% (CI: −1.34 to −0.68), while GDP per capita has increased by 1.82% (CI: 1.78 to 1.86) over the same period. This amounts to a sizable shift in the relative scarcity of ecosystem services vis-a-vis market goods. Ecosystem services have thus become relatively scarcer by 2.83% per year.

4.3 Relative Price Changes of Ecosystem Services

We now combine the two critical pieces—the income elasticity and growth rate estimates—to compute RPCs. Table 10 reports our estimates of RPCs both in the aggregate and for different ecosystem service categories.

Our central estimate for the RPC of aggregate ecosystem services is 1.66% (CI: 1.40 to 1.92). That is, the value of ecosystem services is increasing by around 1.7% per year relative

Table 9 Good-specific growth rates

Indicator	Annual growth rate (S.E.)
Forest area	−0.11% (0.04%)
Living planet index	−2.84% (0.06%)
Red list index	−0.42% (0.01%)
Air quality (PM2.5)	−0.16% (0.17%)
Climate regulation	−1.50% (0.14%)
Aggregate Ecosystem Services	−1.01% (0.17%)
GDP per capita	1.82% (0.02%)

[22] Results are qualitatively similar when constraining the analysis to the most recent trend data, except for air quality regulation which shows a positive development in the current trend data (2010 to 2016), improving by 1.78% per year. In contrast, the decline rate for climate regulation is more strongly negative. Overall, we find a somewhat smaller rate of de-growth of −0.73% for the time period 2010 to 2016. Note that the large decline in the LPI is driven by a small share of species (Leung et al. 2020). We still retain the original LPI data, as how questioning how much weight to put on individual species in a biodiversity index is a normative choice that is not the focus of our analysis here.

Table 10 Relative price changes (RPCs) of ecosystem services

Sample	$\xi = 1/\sigma$(S.E.)	$g_C - g_E$(S.E.)	RPC (C.I.)
Regulating Services	0.60 (0.07)	2.83% (0.17%)	1.71% (1.44% to 1.98%)
Cultural Services	0.65 (0.09)	2.95% (0.09%)	1.91% (1.64% to 2.18%)
Aggregate Services	0.59 (0.07)	2.83% (0.17%)	1.66% (1.40% to 1.92%)
Forest Services	0.66 (0.14)	1.93% (0.04%)	1.27% (0.85% to 1.69%)

Notes: RPCs 95% confidence interval estimates based on $\xi\,(g_C - g_E) \pm 1.96 \times \sqrt{\left(\frac{S.E.(\xi)}{\xi}\right)^2 + \left(\frac{S.E.(g_C - g_E)}{g_C - g_E}\right)^2}$

to market goods. This is substantially larger than the estimate reported in Baumgärtner et al. (2015). The RPC estimate for regulating services is only slightly higher than that for cultural services, which is qualitatively similar to what Heckenhahn and Drupp (2024) find within their German case study. While the income elasticity for forest ecosystem services is higher than for ecosystem services on aggregate, the rate of decline of forest area is considerably smaller; in combination, the RPC of forest ecosystem services (1.27%) is smaller than that of aggregate ecosystem services.

5 Application to Environmental-Economic Accounting

Relative price adjustments of ecosystem services are relevant for both policy appraisal and environmental-economic accounting. Here, we explore implications for accounting, considering the *CWON* 2021 report by the World Bank (2021) as a prominent case to illustrate the approach and its importance with a focus on forest natural capital.[23] We afterwards illustrate implications also for our aggregate measure of ecosystem services.

CWON, like most measures of comprehensive wealth, only features selected natural capital stocks, predominantly relating to fossil energy resources and other provisioning services that are traded on markets. *CWON*, however, also considers non-timber forest benefits as part of its natural capital accounting. Non-timber forest benefits are currently estimated to be around 12% of the total value of natural capital (World Bank 2021). Non-timber ecosystem service values in the year 2018, in WTP per hectare, were based on a meta-regression analysis drawing on 270 estimates from non-market valuation studies of non-timber forest benefits by Siikamäki et al. (2021). Per-hectare values are assumed to be constant over time and only adjusted for inflation by using country-specific GDP deflators (World Bank 2021). The capitalized value of non-timber ecosystem services is calculated as the present value of annual services, discounted over a 100-year time horizon at a constant discount rate of 4%. This implies that no adjustment for RPCs is factored in despite forest de-growth, particularly in comparison to GDP per capita. Implicitly, this carries the assumption that WTP

[23] Drupp et al. (2024a) have subsequently also applied the approach to proposing adjustments for assessing changes to ecosystem services in benefit-cost analysis.

does not increase with income and—in the setting of our model—that ecosystem services are considered perfect substitutes to market goods.[24]

Taking our estimated growth rates for forest area and for GDP per-capita as best estimates of growth rates for the 100 year time horizon in question (see Panel (a) in Fig. 2), we compute RPCs for forest ecosystem services using our disentangled estimate on the income elasticities of WTP for forest ecosystem services (see Panel (b) in Fig. 2). We use the RPC of

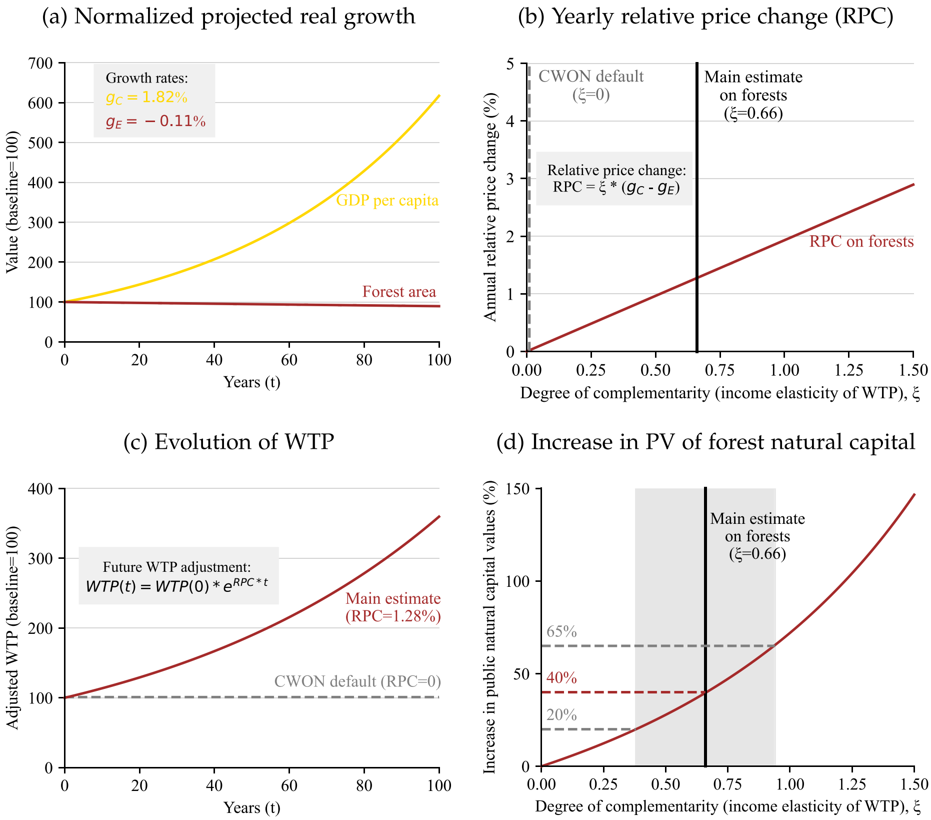

Fig. 2 Accounting for public forest natural capital with changing relative prices. (**a**) Normalized projected real growth. (**b**) Yearly relative price change (RPC). (**c**) Evolution of WTP. (**d**) Increase in PV of forest natural capital. *Notes:* panel (**a**): relative to growth in market goods (or real income, reflected by GDP per capita), global forest area has been decreasing, which we here project forward. Initial values are normalized to 100 in year 0. Panel (**b**): the relative price change (RPC) rule maps growth rates of GDP per capita and of ecosystem services into yearly relative price adjustments against the rate at which WTP for ecosystem services changes with income. Panel (**c**): future WTP adjustment when applying our main estimate for the RPC for forest ecosystem services. Panel (**d**) shows the estimated increase in the changing wealth of nations' (*CWON*) non-timber forest natural capital value (in %), relative to the *CWON*'s standard estimate, as a function of the degree of complementarity between forest ecosystem services and market goods, measured by the income elasticity of WTP (see the maroon line). The vertical black line indicates the central estimate of the income elasticity of WTP for forest ecosystem services, while the grey-shaded area indicates its 95 confidence interval. Horizontal, dashed helplines indicate the corresponding increase in the public natural capital values (in %)

[24] Siikamäki et al. (2021) report positive and significant GDP elasticities of WTP for recreation and habitat/species conservation, for instance, but these are not considered in the *CWON* natural capital valuation.

1.27% to adjust future WTP estimates for increasing income and changing real scarcities of forest ecosystem services (according to Eq. 5, and contrast these yearly adjusted WTPs with the *CWON* default which considers constant real WTPs over the time horizon (see Panel (c) in Fig. 2). Real WTP in 30 (100) years, for instance, would be 47 (260) percent higher as compared to the standard *CWON* analysis, which does not consider RPCs.

We then compute the discounted present value of non-timber forest natural capital (according to Eq. 6, using *CWON*'s discount rate of 4%, and compare it to the unadjusted value from *CWON*. In Panel (d) of Fig. 2, we depict the estimated increase in the non-timber forest natural capital value (in %), relative to the *CWON*'s estimate, as a function of the degree of complementarity between forest ecosystem services and market goods, measured by the income elasticity of WTP for forest ecosystem services (according to Eq. 7). For our central estimate of the RPC of forest ecosystem services, we find that the value of non-timber forest natural capital should be uplifted by 40%, with a 95%ile confidence interval around the income elasticity resulting in a range of uplift-factors of 20 to 65% (see Panel (d) in Fig. 2). Alternatively, Cobb-Douglas substitutability ($\sigma = \xi = 1$) would imply uplifting the present value of non-timber forest ecosystem services by 72%. Another prominent assumption in applied modelling is to use an elasticity of substitution of 0.5 (c.f., Sterner and Persson 2008), i.e., an income elasticity of 2 (off the chart here), which would translate into uplifting the public natural capital value by around 280%.

Considering the limited degree of substitutability and shifts in relative scarcity by performing RPC adjustments in computing the natural capital value of non-timber forest services makes a material difference to natural capital accounting in *CWON*. The 40% increase in non-timber forest value would lead to an increase of the overall natural capital value in *CWON* of around 5%.

Beyond the *CWON* case study, we illustrate implications also for our aggregate measure of ecosystem services. Using the RPC of aggregate ecosystem services, which draws on a slightly lower income elasticity of WTP but a larger difference in growth rates, due to a stronger decline in aggregate ecosystem services, we obtain a central uplift-factor for public natural capital of 58% (see Fig. 3), which amounts to a 45% increase as compared to the *CWON* uplift factor. When changing the discount rate from *CWON*'s 4% to a rate of 2%, as per current guidance in US Circular A-4 and as recommended by most experts (Drupp et al. 2018), we find that the public natural capital value should be uplifted by around 97% instead of solely 58% according to our main estimate for the income elasticity of WTP (see Fig. 3).

6 Discussion

The value of future non-marketed ecosystem services today depends on the future state of the world in terms of consumption growth and the evolving scarcity of ecosystem services. These future ecosystem values/shadow prices also depend on societal preferences for ecosystem services and how substitutable they are with regular consumption goods. Given this, estimating the trajectory of shadow prices for ecosystem services requires a theoretical structure that can be calibrated to capture changes in relative scarcity over time and embody the effect of substitutability on shadow prices. In this paper we have assumed CES preferences and calibrated these social preferences via an extensive meta-analysis. The degree of substitutability/complementarity is proxied by the inverse of the income elasticity of WTP

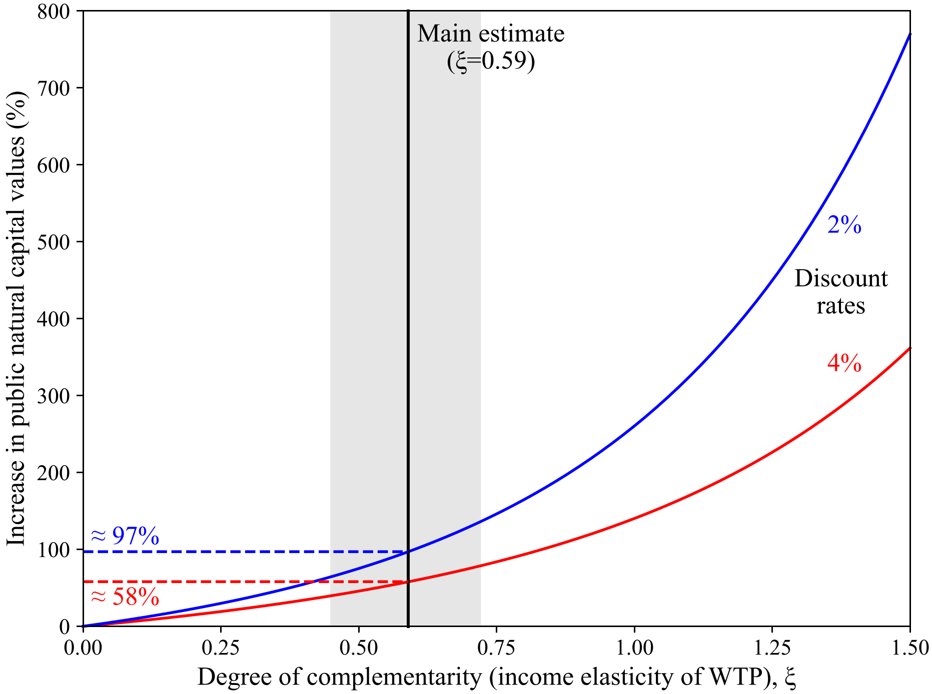

Fig. 3 Increase in public natural capital values along the degree of complementarity. *Notes:* Estimated increase in public natural capital values for our aggregate assessment of ecosystem services (in %), relative to a case where RPCs are not considered, as a function of the degree of complementarity between ecosystem services and market goods, measured by the income elasticity of WTP for ecosystem services. The red and blue lines illustrate effects for different discount rates of 4% (red, as in CWON guidance) and 2% (blue, as in US circular A-4). The vertical black line indicates the central estimate of the income elasticity of WTP for our aggregate assessment of ecosystem services, while the grey-shaded area indicates its 95 confidence interval. Horizontal, dashed helplines indicate the corresponding increase in the public natural capital value (in %)

for ecosystem services following Ebert (2003). This parameter is then estimated using 735 income-WTP pairs from our meta-analysis of the peer-reviewed literature. The wide range of studies allows use to calibrate shadow prices and their trajectory over time for both aggregated and sub-categories of ecosystem services. The theoretical structure and empirical approach that we use can certainly be improved in the future along a number of dimensions, some of which we sketch below. Despite this, our estimates of the RPCs for ecosystem services are likely to be conservative and sufficiently robust for policy applications.

In the following, we discuss some specific shortcomings of our study that could be addressed in future work.

First, our analysis is subject to common concerns regarding the contingent valuation method, e.g. hypothetical bias and related issues. These concerns have been extensively discussed in the literature (e.g., Kling et al. 2012). Schläpfer (2008), for instance, argues that income effects in contingent valuation studies are likely to be too small as a result of anchoring biases. The absence of a clear empirical test for this hypothesis makes it difficult to substantiate this claim. Yet, if this were the case, we would underestimate income elasticities, consequently underestimating the degree of complementarity, and our estimates of the upward-adjustment of natural capital values would be too conservative. Future work should seek to identify income elasticities using other valuation techniques, and also in incentivized settings.).[25]

Second, besides the specific concerns associated with contingent valuation, our approach to identifying the (aggregate) income elasticity of WTP—while building on the state of the art in the literature—is somewhat coarse, and rests on a very heterogeneous, imbalanced panel.[26] Like Heckenhahn and Drupp (2024) and contrary to other similar meta-analysis, e.g., Jacobsen and Hanley (2009), we do not impose restrictions on the type of ecosystem service valued in each study. This comprehensive approach has clear advantages, such as a very large sample size that far exceeds those of previous meta-analyses in the field. On the other hand, it raises concerns about the comparability of individual WTP estimates across a wide range of ecosystem services. This limited 'commodity consistency' (e.g., Bergstrom and Taylor 2006; Moeltner and Rosenberger 2014), is a key feature of our analysis, as we seek to obtain an aggregate measure of the elasticity across all ecosystem services as well as measures for key ecosystem service sub-types than can be used as reasonable proxies for performing RPC adjustments to future WTP estimates. To mitigate concerns about limited comparability—to the extent possible—we control for a number of covariates at the WTP observation-level and also present disaggregated results by the ecosystem service categories for regulating and cultural services of the MEA (2005) in our main results section. Still, substantial heterogeneity persists due to the varied units of measurement within ecosystem service categories. Moreover, our sample contains studies that reflect both methodological refinements that have been introduced over time, which may have arguably reduced inflated WTP estimates (Barrio and Loureiro 2010), and an increasing share of studies from Asia and lower-income countries over time. Ideally, we would like to identify the income elasticity of WTP based on a sample that is not subject to methodological revisions or major changes in its geographical composition. While a few test-retest investigations exist that repeatedly draw from the same sample (see Skourtos et al. 2010), for an overview), these typically concern shorter time frames and have not been designed to investigate income effects. Evidence to date suggests that mean WTP estimates are relatively constant for up to five years, but that this is not the case for longer time frames (Skourtos et al. 2010). In our meta-analysis, we find that the income elasticity of WTP appears relatively stable across decades. Relatedly, the underlying CV studies often elicit income only on coarse interval scales, which necessitates some subjective choice on generating an appropriate mean income estimate. To explore sensitivity with respect to top and bottom income observations, as well as to outliers more generally, we run further sensitivity analyses (reported in Figs. 9, 10 and 11 in Appendix D) and find that our main estimate is reasonably robust to these variations.

Third, our approach of relying on a direct relationship between the income elasticity of WTP and the elasticity of substitution or complementarity holds under a very common but still very specific assumptions on preferences, specifically that preferences are represented by a CES utility function (e.g., Ebert 2003; Baumgärtner et al. 2017a), and that marginal

[25] Recent work contrasting incentivized and hypothetical experiments to study substitutability preferences directly does not suggest a major role of hypothetical bias for the elasticity as such, but documents hypothetical bias for other environmental preference measures (Drupp et al. 2024b).

[26] While a balanced, homogeneous panel suitable for estimating income elasticities of WTP for aggregate ecosystem services does not currently exist—and is unlikely to be feasible in practice—we include this discussion to highlight the limitations of the available data.

WTP is well approximated with a first-order Taylor series expansion (for a discussion, see Smith 2023). While we are not aware of studies that systematically assess the relative goodness-of-fit of CES versus alternative utility specifications, Conte et al. (2025) provide theoretical arguments and empirical evidence suggesting that the assumption of constant substitutability in CES specifications is inadequate under evolving species scarcity, which calls into the question the assumption of homothetic preferences implied by CES.)[27] Beyond that, the applied theoretical literature provides extensions to the CES framework. One interesting case is an extension of preferences that consider critical thresholds in the form of subsistence needs (Heal 2009; Baumgärtner et al. 2017b; Drupp 2018). If there exists some critical level of ecosystem services, $\overline{E} > 0$, then the degree of substitutability becomes endogenous to the level of the ecosystem service over and above the critical level, and the RPC equation is adjusted to (cf. Drupp 2018):[28] $RPC_t = \xi \left[g_{C_t} - g_{E_t} \frac{E_t}{E_t - \overline{E}}\right]$. Such an extension implies higher RPCs that increase substantially as one gets close to the critical threshold given exogenous growth rates (Drupp 2018). It would lead to an upward revision of the natural capital values adjustment discussed in Sect. 5. However, if growth rates are endogenous and optimally managed, this would help ensure that such critical subsistence levels are not reached and RPCs are not substantially affected (Drupp and Hänsel 2021).

Fourth, we assume that preferences elicited primarily on small-scale projects aimed at improving ecosystem service conditions scale up to the global level. However, services may be perceived as complements (substitutes) at the local level, but as substitutes (complements) at a global scale, or vice versa. This issue may be more pronounced when the focus is put more on local public goods as compared to global public goods.

Fifth, we have further updated and extended the *"Herculean task"* (Baumgärtner et al. 2015, p. 278) of assembling a proxy for the aggregate growth rates of ecosystem services. There exists no accepted standard for how to aggregate various measures of environmental quality, and also the data sources we draw on have to be considered imperfect proxies themselves. We have followed Baumgärtner et al. (2015) in using the unweighted arithmetic mean of the growth rates for the different types of ecosystem services. This assumes that the elasticity of substitution between different ecosystem services is equal to one (Cobb-Douglas), which implies that WTPs would be the same for all types of ecosystem services if their quantities were similar, an assumption we cannot properly test. We note that there are other conceivable means of aggregation, using different weightings to different degrees of substitutability. We leave a systematic exploration of this issue to future work; the same holds for exploring the role of uncertainty around projecting past growth estimates into the future (Gollier 2010). We note, however, that the issue of aggregation not just pertains to different types of ecosystem services but may also be pervasive within ecosystem service types. As a case in point, we consider different types of forests. These show remarkably different recent historical growth rates, ranging from −0.42% per year for tropical forests to 0.44% for sub-tropical forests, with boreal forests largely stagnating (with a growth rate of

[27] Note also in this context that some studies have documented non-constant income elasticities of WTP along income levels (e.g., Barbier et al. 2017), for which we also find some support.

[28] WTP estimates are typically assumed to be a function of the ecosystem service level themselves (Baumgärtner et al. 2017a). Empirical evidence, however, is mixed—Barrio and Loureiro (2010) and others find, for instance, that WTPs decrease with forest cover, while Taye et al. (2021) find that WTPs increase with forest cover—as it's often challenging to isolate the pure effect of the level of the ecosystem service.

0.04%). We therefore consider how tropical versus non-tropical forest natural capital values may need differentiated adjustments over time and, to this end, also re-run our elasticity models by splitting at a country's majority of forest share (see Appendix F). We find that the income elasticity of WTP does not materially differ across these two forest types (0.64 versus 0.62). Differences in relative price adjustment thus mainly derive from the differences in growth rates. In Fig. 12 in the Appendix, we illustrate how public natural capital values for both types of forest may need to be adjusted. For our central estimate, this adjustment amounts to 49% for tropical forests and solely 32% for non-tropical forests.

Finally, our analysis has followed prior literature in estimating historical growth rates of GDP and proxies for ecosystem services while assuming that these (constant exponential) growth rates will continue into the future (Baumgärtner et al. 2015; Drupp 2018). In general, however, the growth rates of both goods may be interdependent and they will be endogenous to environmental management and public policy more broadly. Examples of RPCs in the presence of an endogenous management are studied in integrated climate-economy assessment models (e.g., Sterner and Persson 2008; Bastien-Olvera and Moore 2021; Drupp and Hänsel 2021). Examples of interdependencies include capitalization effects of ecosystem service changes in human-made capital and GDP. For instance, air pollution has been shown to harm not only human health but also economic productivity (e.g., Fu et al. 2021). Reductions (improvements) in air quality may thus lead to lower (higher) GDP growth. Similarly, interdependencies arise in the case of climate regulation and its capitalization in housing prices, such as due to sea level rise, or in the case of groundwater and its capitalization in farmlands (Fenichel et al. 2016). If strong enough, such interdependencies can even lead to a convergence of ecosystem service and human-made goods growth rates, as the scarcity and limited substitutability of ecosystem services as intermediate inputs to production may manifest itself as a sizable drag on growth (Zhu et al. 2019). This would imply that RPCs would become smaller over time, as the limited substitutability in production would become the dominant effect. In our application (see Fig. 2) this could be captured, in terms of its first-order effect, by considering a lower or a declining growth rate of GDP. Beyond this, it would require explicit integrated modeling of the interdependencies. Such an integrated analysis would have to consider not only that ecosystem services affect economic growth, $g_C(g_E)$, as considered in Zhu et al. (2019), but also that economic growth affects ecosystem services, $g_E(g_C)$, an effect illustrated in Gollier (2010). Such interdependencies may thus lead to higher or lower RPCs as compared to the independence case illustrated in this paper.

7 Conclusion

We present a large global database to estimate the degree of complementarity of ecosystem services vis-a-vis human-made goods, via the income elasticity of WTP for ecosystem services, in order to compute RPCs of ecosystem services. We estimate an income elasticity of

WTP of around 0.6, though this differs across ecosystem service subtypes, time frames and continents. The 95% confidence interval excludes the Cobb-Douglas case and suggests a mildly substitutive relationship between ecosystem services and market goods. This finding aligns well with the results of most similar meta-analyses, which mostly derived income elasticity estimates below unity (e.g., Hökby and Söderqvist 2003; Liu and Stern 2008; Jacobsen and Hanley 2009; Lindhjem and Tuan 2012; Subroy et al. 2019). However, it contrasts with complementarity assumptions made in applied modelling (e.g., Sterner and Persson 2008).

For our aggregate assessment of ecosystem services, including estimates of growth rates, we find RPCs of ecosystem services of around 1.7% per year. RPCs are smaller (1.3%) for forest ecosystem services as these show a slower rate of de-growth as compared to other ecosystem service components. We also developed a simple approach for how these estimates can be employed to adjust future WTP estimates and present values to be used in environmental-economic accounting as demonstrated here, or in project appraisal (as subsequently used in Drupp et al. 2024a). In an application on natural capital valuation, taking the *CWON* 2021 report by the World Bank (2021) as a case study, we show that adjusting natural capital estimates for non-timber ecosystem services for RPCs results in uplifting the present value over a 100-year period by around 40%, materially elevating the role of public natural capital. The corresponding estimates for relative price adjustments for our aggregate assessment of public natural capital are more substantial, amounting to between about 43 and 71% for our main estimate of the income elasticity, depending on the social discount rate used. This echoes work on the importance of limited substitutability in climate policy appraisal (Sterner and Persson 2008; Bastien-Olvera and Moore 2021; Drupp and Hänsel 2021; Bastien-Olvera et al. 2024).

While the RPC and value adjustment techniques we present are, in approximation, generally applicable for environmental-economic accounting as well as for project appraisal, the specific numerical inputs, such as elasticities or growth rates, need to be adjusted on a case-by-case basis. We have shown, among others, that elasticities show non-negligible variation across ecosystem service types, across continents and cross-country income levels. We thus regard our study as an important step towards developing a valuation toolkit for governments to apply and use in different contexts and for different ecosystem services. Here, we have provided evidence from one valuation method, contingent valuation. Further investigations should assess the heterogeneity in income and substitution elasticities, as well as of good-specific growth rates, more broadly also drawing on other valuation approaches, such as choice experiments of various revealed preference elicitation techniques.

Overall, our results suggest that the case for making RPC adjustments is reasonably robust and that more countries and institutions than present (Groom et al. 2022) should consider making such adjustments to correct the current mis-valuation of non-market goods in public policy appraisal and of public natural capital values in comprehensive wealth accounting.

Appendix A. Selection of Relevant Valuation Studies

A.1. PRISMA Flow Diagram

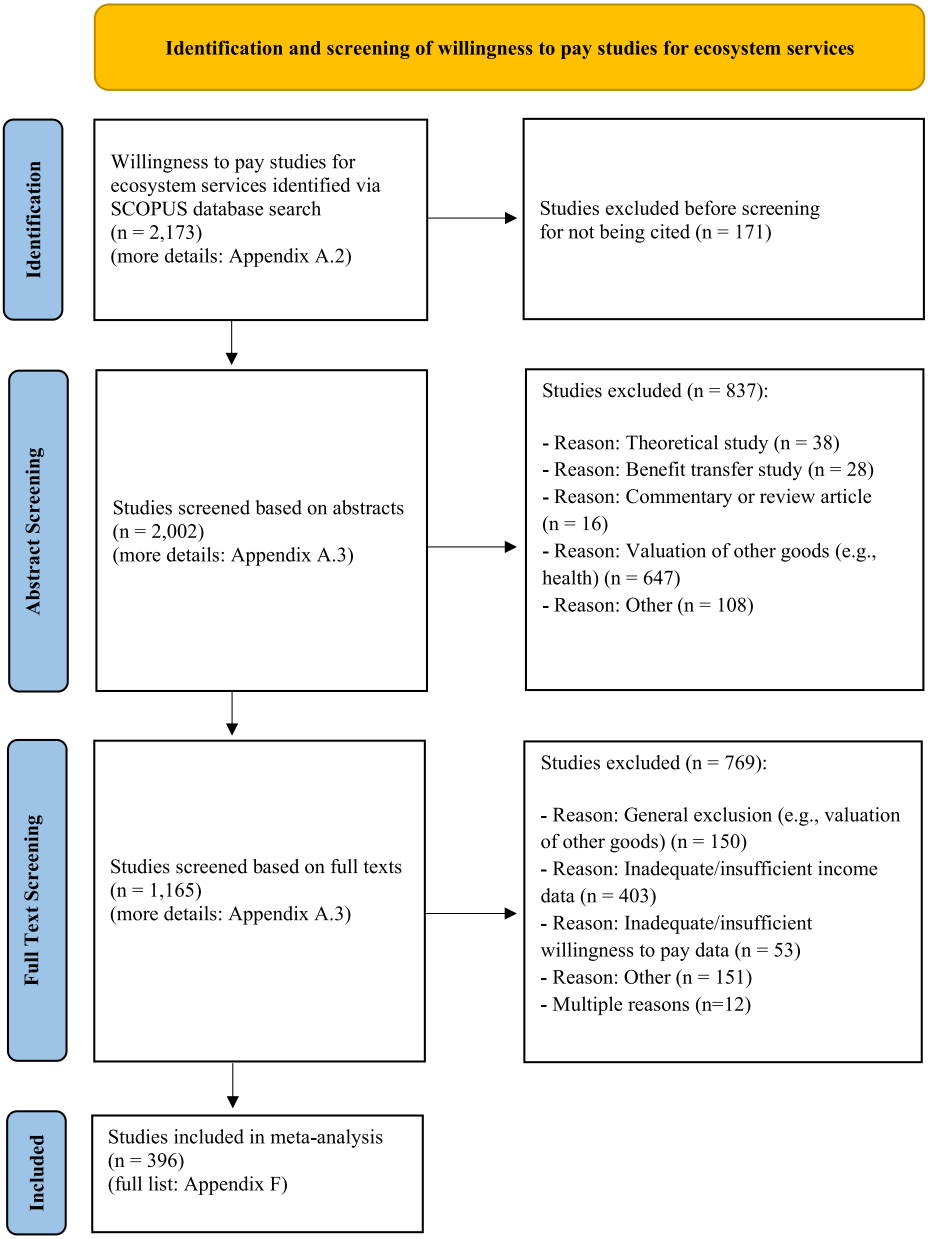

Fig. 4 PRISMA flow diagram of the study identification and screening process. Framework adapted from Page et al. (2021)

A.2. Search String

Our focus is on values for regulating ecosystem services and cultural ecosystem services (not provisioning services) that have been elicited using the contingent valuation method. The search string has three components (1) focus on ecosystem services, (2) focus on WTP estimates, (3) focus on the contingent valuation method.

(TITLE-ABS-KEY (environment* OR natur* OR ecosystem OR biodiversity OR biologic* OR ecologic* OR habitat* OR forest* OR species OR protected OR conserv* OR endangered OR "national park*" OR landscape* OR terrestrial OR pollination OR tree* OR tropic* OR vegetation OR peatland* OR grassland* OR dryland* OR pastoral OR soil OR animal* OR bird* OR wild* OR air OR water OR aquatic OR marine OR coast* OR water* OR fish* OR wetland* OR mangrove* OR reef* OR marsh* OR floodplain* OR river* OR climate OR storm* OR erosion OR pest* OR hazard* OR recreat* OR touris* OR "urban green" OR sacred OR spirit* OR sanctuary OR "natural heritage" OR aesthetic*)

AND TITLE-ABS-KEY (wtp OR willingness-to-pay OR "willingness to pay*" OR "willing to pay*" OR "shadow price*" OR "shadow value*" OR "implicit price*" OR "implicit value*")

AND TITLE-ABS-KEY ("contingent valuation*" OR cvm OR "contingent choice*"))

AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014) OR LIMIT-TO (PUBYEAR , 2013) OR LIMIT-TO (PUBYEAR , 2012) OR LIMIT-TO (PUBYEAR , 2011) OR LIMIT-TO (PUBYEAR , 2010) OR LIMIT-TO (PUBYEAR , 2009) OR LIMIT-TO (PUBYEAR , 2008) OR LIMIT-TO (PUBYEAR , 2007) OR LIMIT-TO (PUBYEAR , 2006) OR LIMIT-TO (PUBYEAR , 2005) OR LIMIT-TO (PUBYEAR , 2004) OR LIMIT-TO (PUBYEAR , 2003) OR LIMIT-TO (PUBYEAR , 2002) OR LIMIT-TO (PUBYEAR , 2001) OR LIMIT-TO (PUBYEAR , 2000)) AND (LIMIT-TO (LANGUAGE , "English"))

A.3. Exclusion and Selection Criteria

A.3.1. Paper Exclusion Criteria

Citations: We excluded all studies that had not been cited (in SCOPUS).

Abstract screening: We excluded non-topical publications based on abstract-screening that do not report new primary WTP estimates. Specifically, we excluded: Theory, reviews, comments, non-primary valuation (such as benefit transfer), as well as WTPs for non-environmental goods, WTPs for provisioning services, WTPs derived from valuation approaches other than CV.

PDFs obtainable: We excluded studies where we could not access the PDFs.

Paper screening: We excluded non-topical publications based on paper-screening that do not report new primary WTP estimates. Specifically, we excluded: Theory, reviews, comments, non-primary valuation (such as benefit transfer), as well as WTPs for non-environmental goods, WTPs for provisioning services, WTPs derived from valuation approaches other than CV.

Overall, our approach to WTP studies is intentionally inclusive to ensure that our meta-analysis accurately captures the full range of values associated with ecosystem services. Some included studies may not explicitly refer to ecosystem services, however, in the respective cases, we deemed it reasonable to assume that study participants associated ecosystem services with the value of the goods being assessed (e.g., we generally assumed renewable energy to be associated with climate regulation in people's minds).[29]

A.3.2. Data Selection Criteria

In the following, we detail our approach for selecting WTP and income values, which constitute the key variables for our analyses.

WTP data selection: We exclude median WTP values, WTP values derived from multiplying marginal WTP estimates, WTP values resulting from the addition of preceding WTP values, WTP values based on pretests, WTP values based on subsamples when overall mean values are provided, and per-use WTP values. When different results are presented based on different models, we include only the WTP values from the standard model. If no standard model is indicated, we average the relevant model results. When multiple mean WTP estimates are provided (e.g., including or excluding outliers and zero bids), we include the estimate marked as the authors' preferred estimate. If no preference is indicated, we include the unmodified estimate. When WTP values are provided for different subsamples, we assign the WTP values to the corresponding subsample income values. When WTP values refer to a monthly payment, we multiply these values by 12 to obtain annual values. WTP values referring to yearly payments and one-time payments are included as they are. When WTP results are divided among different quantities (supply levels) of the same ecosystem service, we take the most marginal of these values, though alternatives of taking their average or including all levels as separate estimates are also considered. If WTP results consider participants' response uncertainty, we average these values. When WTP results are split among different subsamples without overall mean WTP values or subsample-specific income values, we take the average of the subsample WTP values, using weighted averages if subsample sizes are available.

The inclusion of negative WTP values results in the inclusion of one additional estimate. In the relevant study, four estimates are provided where one is negative but statistically insignificant from zero at standard levels of evaluation. Exclusion of the negative WTP estimate and inclusion by two separate approaches results in a slight impact. Our method of inclusion is by transforming the negative estimate as $-ln(abs(WTP_{ij}))$ and then proceeding with our estimation strategy as in the main text. The alternative method is to substitute $ln(0.0001)$ for the negative estimate and include an indicator variable equal to one for the observation.

[29] The decision for inclusion was particularly challenging for studies estimating non-market ecosystem service values embedded in otherwise market goods. For example, in Kim et al. (2019) and Milovantseva (2016), non-market ecosystem service values related to climate and air quality regulation, and water pollution and waste regulation, respectively, are suggested during the creation of market goods - cell phones. The authors, however, take care to isolate ecosystem service-relevant components by framing their survey prompts relative to baselines of otherwise similar devices without the ecosystem service component. On this basis, we decided to include these studies in our analysis.

The exclusion of per-use values is necessary when studies do not—as in every case we encounter—report on a per-respondent basis how many times respondents use the studied ecosystem service over an identified period of time such as a year. The number of uses may differ substantially from any mean usage estimate. As such, the excluded per-use estimates (around 80 observations) cannot be placed on a comparable timescale to our included estimates.

Income data selection: We include studies regardless of whether they provide net or gross income data, while we contacted study authors when articles did not provide specific information on that. We also included studies regardless of whether the respective income data refers to the household or personal level. If a study only provides percentage shares of income categories instead of a mean income value, we derive the mean income value by calculating the midpoints of the income categories and multiplying them by their respective percentage shares. For the category open towards the bottom, we multiply the upper bound (the lower bound of the lowest income category) by 0.75 to find the midpoint, and for the category open towards the top, we multiply the lower bound (the higher bound of the highest income category) by 1.5. We then sum these products and divide by the sum of the percentage shares to estimate the mean income. For income values split among different subsamples, we average these values to attain overall mean income values, using weighted averages if subsample sizes are available.

Recognising that the top and bottom income category multipliers (0.75 and 1.5, respectively) are judgment calls, we test the sensitivity of our results to alternatives. We do so by iterating over lower-income category multipliers of 0 to 0.9 and over upper-income category multipliers of 1.0 to 1.9 in increments of 0.1. In all cases, income elasticity of willingness to pay estimates change by less than three-percent. As the lower- and upper-income categories apply to small groups of the population in most studies—and is apply equally to all relevant studies—it is unsurprising that results are insensitive to this adjustment.

Appendix B. Graphical Presentation of the Meta-analysis Data

Figure 5 visualizes the meta-analysis data using the original, untransformed income and WTP data in the upper panel. Here, each dot represents a WTP value. In contrast, the lower panel presents both WTP and income data in their logarithmic forms, which we consistently use throughout our main analysis to calculate income elasticities. Here, each dot represents a ln(WTP) value. The lower panel also includes a regression line based on the univariate version of our preferred square root of sample size weighting regression model.

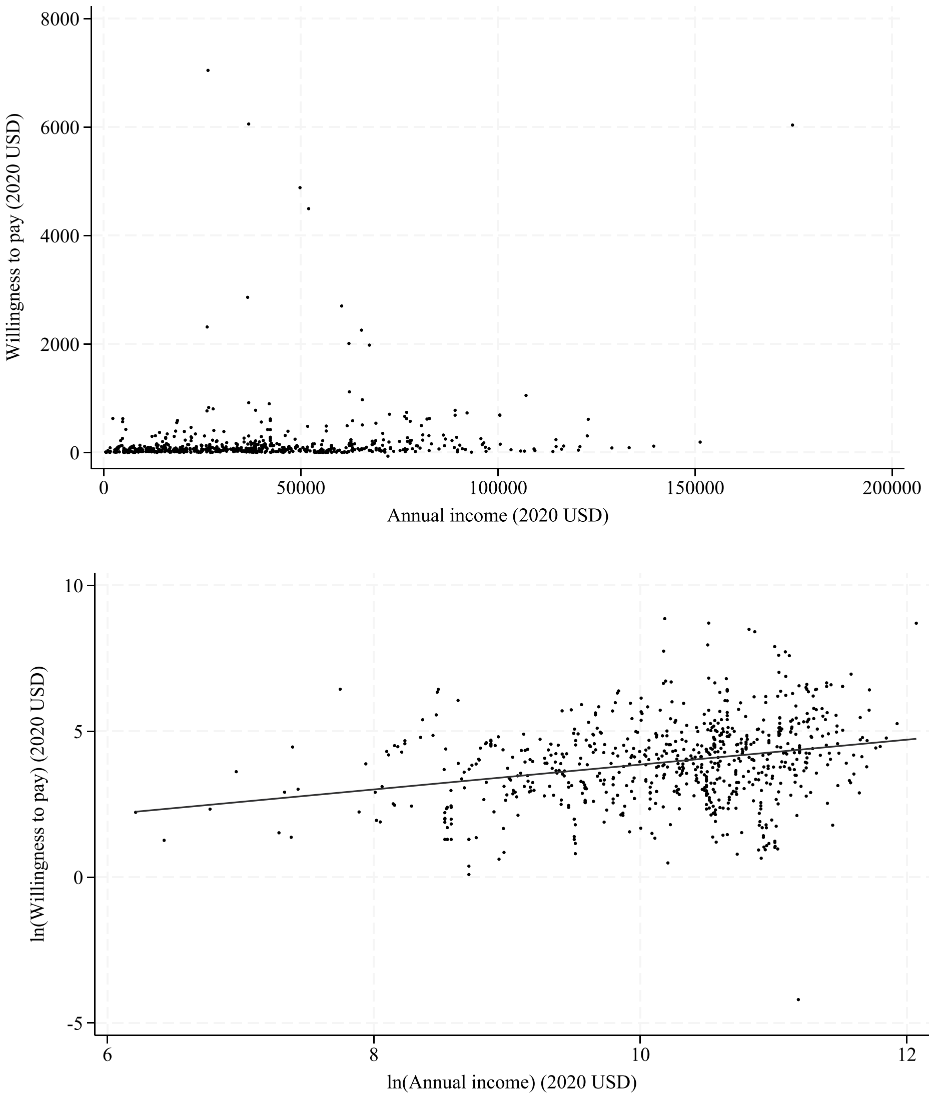

Fig. 5 Visualization of mean income and WTP data (original and ln-transformed)

Appendix C. Inflation and Currency Conversion

All monetary values were converted to 2020 US Dollar by first inflating the respective national consumer price index and then applying purchasing-power-parity (PPP) conversion. The relevant year for the inflation of the values was the year of study data collection. When the authors did not provide the study year, we estimate the average lag between study and publication years based on the studies where both pieces of information is available. The difference is approximately 4.0 years on average. We use this to estimate the study year when missing. When historical inflation data for years far in the past were unavailable, we utilized the most recent year's inflation data as an estimate for these years' inflation rates.

Appendix D. Alternative Specification Results

This section presents alternative specifications to explore the robustness of our results. We first present a specification graph to suggest the robustness of our results to the inclusion or exclusion of covariates. Second, we present results based on alternative statistical models (fixed-effects, random-effects, weighted and unweighted OLS) to suggest the robust of our results to model selection.Third, we present the sensitivity of results to alternative weighting methods. Fourth, we test the sensitivity of results to dropping successively larger portions of the dataset in terms of top and bottom incomes, in turn. Finally, we test the sensitivity of results to randomly dropping successively larger shares of the dataset.

We test $2^{15} = 32,768$ alternative specifications based on including or excluding variables and report the results as a specification graph. Alternatives potentially include the covariates in our main specification, plus respondent age, household size, survey format, continent, time period (pre- versus post-2011), and whether the study pertains to forests. Inclusion of the MEA list of regulating and cultural services indicators variables is treated as one group (either included or excluded together) rather than individually to avoid running alternative specification on 2^{26} combinations.

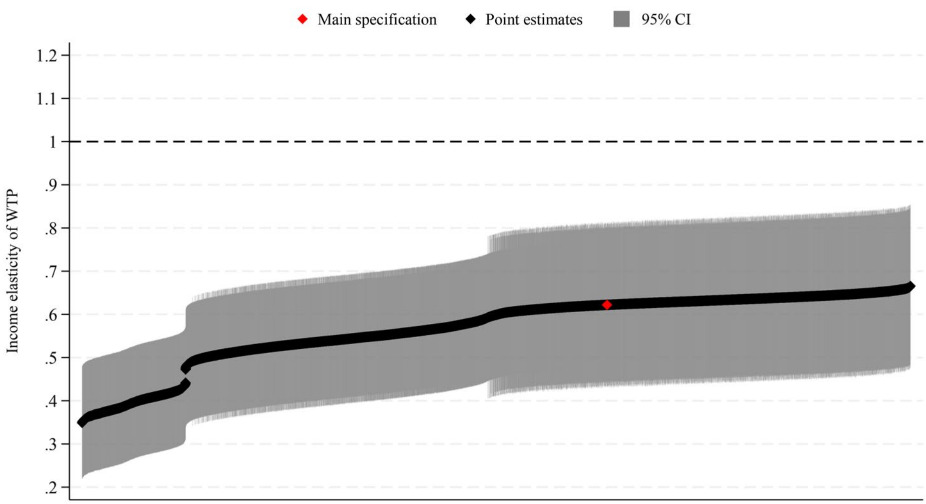

Fig. 6 Income elasticity of WTP estimates based on alternative model specifications. *Notes:* Estimates are the result of $2^{15} = 32,768$ alternative specifications of Eq. 8. The main specification is based on Eq. 8 which is at the 63rd percentile ranking of our income elasticity coefficient estimates from smallest to largest. The 95% confidence interval estimates are included and results are plotted from smallest (0.35) to largest (0.67) coefficient estimate on $ln(INCOME)$

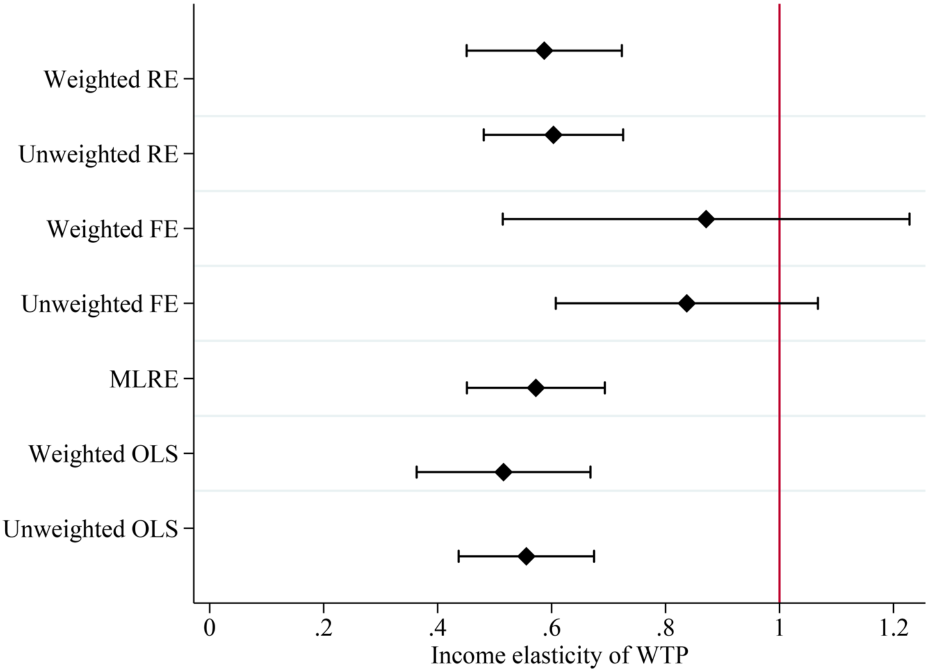

Fig. 7 Income elasticity of WTP estimates based on alternative statistical models. *Notes:* The main result is based on a random-effects (RE) model weighted by the square root of the sample size. Some frequent alternatives to this approach include unweighted random effects, multi-level random-effects (MLRE), and both OLS and fixed effects models that are weighted and unweighted. While a Hausman test suggests RE model is most appropriate, we provide these alternative estimates

We find that the regression model chosen also impacts results. Our main specification utilises a random-effects model which also falls between the fixed effects and OLS (and between effects) estimators. However, the fixed-effects alternative would also be derived with substantially less data as it excludes and singleton estimate studies.

We also find an impact from choosing alternative weighting schemes. Follow common convention, we prefer the square-root of the sample size of studies to develop as weights. This places more weight on larger studies but without allowing large studies to entirely dominate the results. In effect, this results in a smaller estimate of the income elasticity of WTP and subsequently a more conservative RPC estimate.

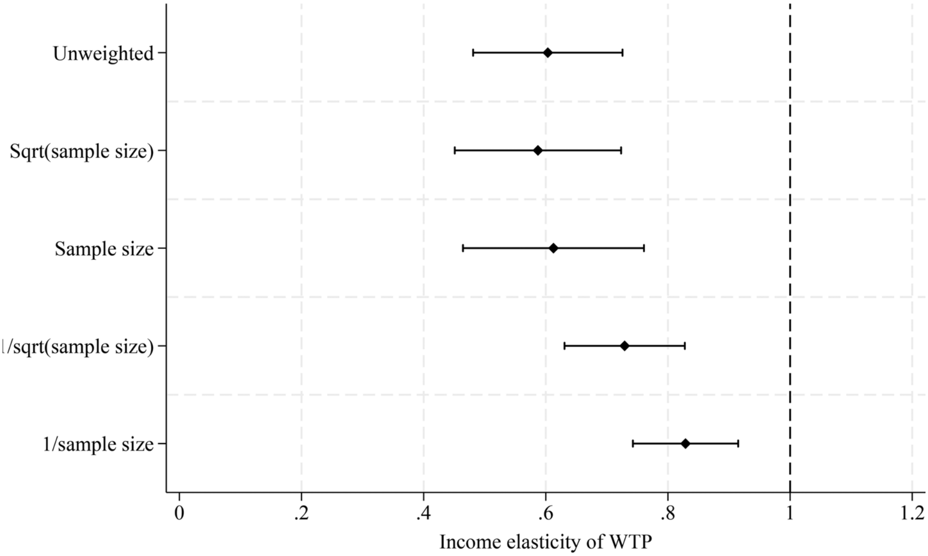

Fig. 8 Income elasticity of WTP estimates by weight selection. *Notes:* The main result is derived with weights based on the square root of the sample size. Some alternatives that are more or less reasonable are to use the sample size, inverse of the sample size, and inverse of the square root of the sample size. Inverse sample sizes will tend to place more weight on studies with smaller sample sizes and squared sample size weights will tend to bias estimates toward studies with substantially larger samples

We drop successively larger portions of the dataset at the top and bottom ends to test the sensitivity to outliers. We take this exercise through all top (bottom) income levels from the top (bottom) 1-percent through the bottom (top) 90-percent. We find that in both cases, a larger share – about one-third – of the data would have to be dropped before markedly different income elasticity of willingness to pay estimates would be arrived at.

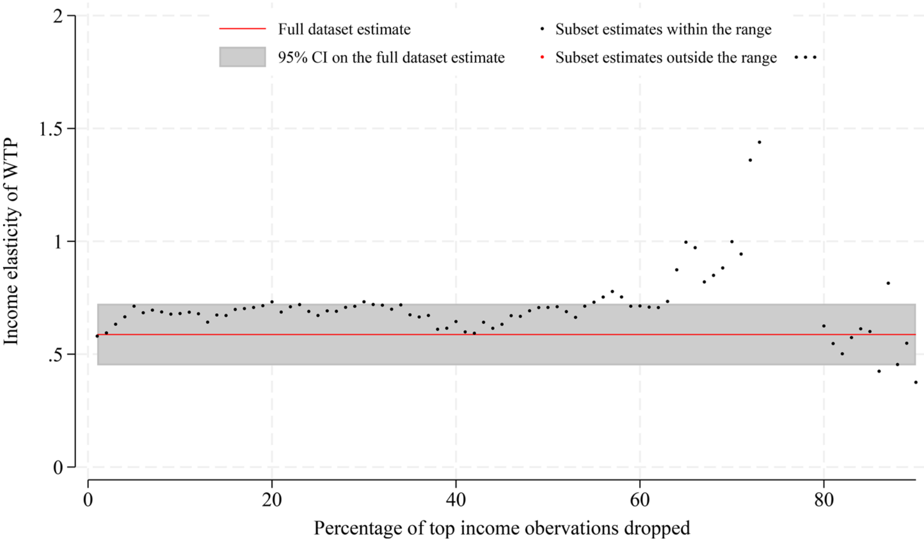

Fig. 9 Income elasticity of WTP estimates when dropping top income observations. *Notes:* Alternative estimates are the result of dropping a successively larger share of observations ranked by respondent income. We first drop observations with the top 1-percent of incomes, then proceed in 1-percent increments, dropping the top 2-percent, then 3-percent, and so on up to 90-percent

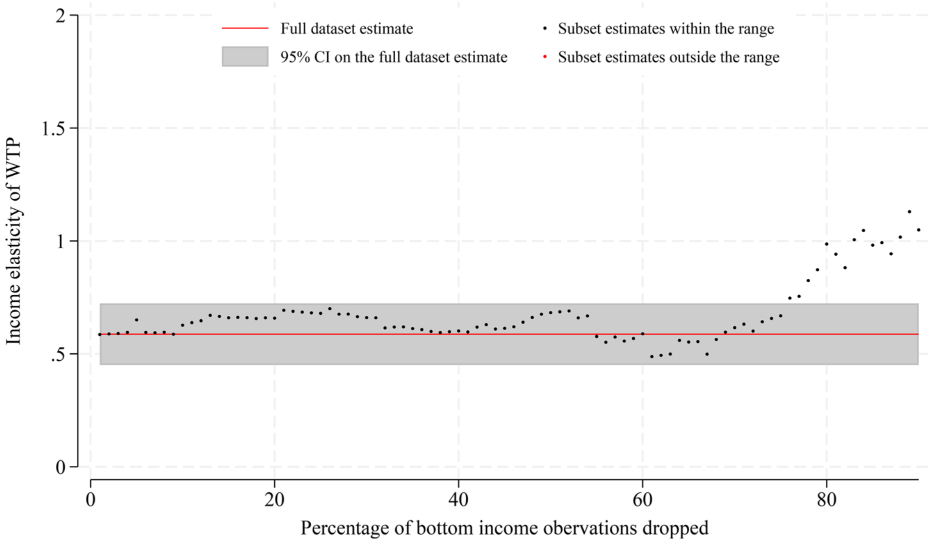

Fig. 10 Income elasticity of WTP estimates when dropping bottom income observations. *Notes:* Alternative estimates are the result of dropping a successively larger share of observations ranked by respondent income. We first drop observations with the bottom 1-percent of incomes, then proceed in 1-percent increments, dropping the bottom 2-percent, then 3-percent, and so on

Finally, we randomly drop successively larger shares of our dataset to test whether subsets are driving our results. We randomly select and drop data 25 times at each percentage level, from dropping 1-percent of the data through 90-percent −2,250 draws in total. As in top- and bottom-income dropping exercises, we find that a substantial share of the data must be dropped to substantially impact the results.

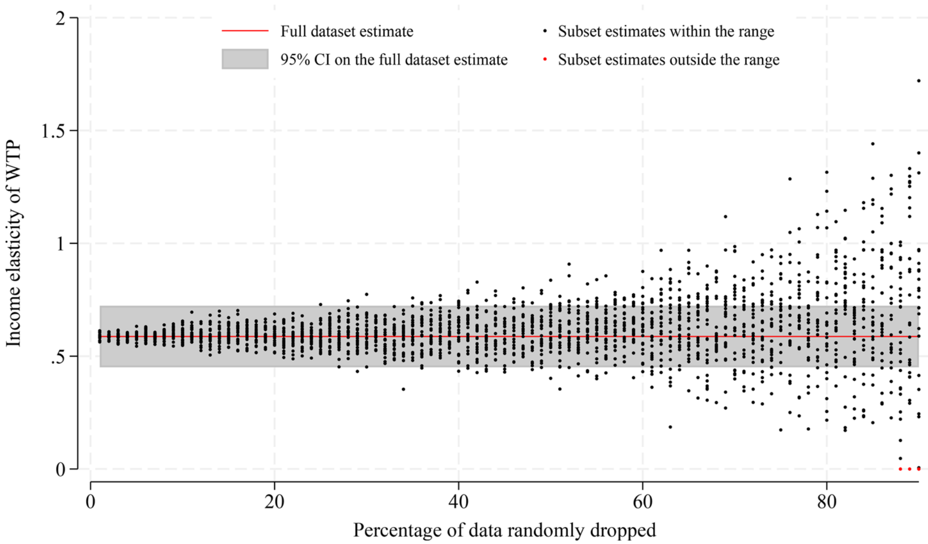

Fig. 11 Sensitivity of income elasticity of WTP estimates to randomly dropping data. *Notes:* Alternative estimates based on dropping random draws of the dataset. At each 1-percent increment, 25 draws of the data are used to re-estimate the income elasticity of WTP using our main model specification. Data is randomly drop in successively larger amountds from 1-percent through 90-percent of the data in 1-percent increments

Appendix E. Adherence to Best Practice Recommendations

In this appendix, we outline how our meta-analysis aligns with best practice recommendations for meta-regression analysis by Stanley and Doucouliagos (2012). Each subsection summarizes how we implement the key recommendations from individual book chapters that are particularly relevant to our meta-analysis.[30]

Chapter: Identifying and Coding Meta-analysis Data

Stanley and Doucouliagos (2012) summarize key recommendations for identifying and coding meta-analysis data on p. 37. Overall, we largely adhere to these guidelines. Firstly, we follow a transparent, systematic, and inclusive procedure to select studies. Secondly, we defined inclusion and exclusion criteria ex-ante and explicitly documented the search and study selection steps, including the use of a PRISMA flow diagram (see Appendix A.1). Thirdly, we apply a replicable coding approach and comprehensively coded various potentially influential aspects on the study level, such as elicitation format and payment vehicle. To further ensure replicability, we provide both the dataset and the STATA code along with this paper. Finally, we systematically checked for data and coding inconsistencies during the dataset generation and coding process.

Chapter: Summarizing Meta-analysis Data

The main recommendations for summarizing meta-analysis data are given on pp. 49–50. We present detailed descriptive summaries of key variables, including distributions by geographic region and ecosystem service category. In the main text, we summarize descriptive statistics using tables (see Tables 1 and 2), while in the Appendix we provide graphical representations (see Fig. 5). In addition, we examined the data for outliers and assessed their validity.

Chapter: Explaining Economics Research

The main recommendations on explaining economics research, primarily focused on statistical modeling, can be found on pp. 104–105. In line with these recommendations, we apply a range of statistical models, including random-effects, fixed-effects, OLS, and the MLRE model, to check the robustness of our results (see Fig. 7). Furthermore, we apply the Hausman test to inform our choice between random-effects and fixed-effects models. Also, we use multivariate meta-regression analyses, thus controlling for relevant confounders. However, we do not employ a general-to-specific modeling strategy. We consistently report results using our preferred set of control variables and assess robustness by comparing models with and without these controls.

[30] Note that we do not include the recommendations on addressing publication bias here. While we acknowledge the importance of addressing publication bias in general, we do not conduct publication bias tests in this study. This is because our income elasticity estimates are derived from reported mean WTP and income values, rather than from regression-derived effect sizes. As such, the typical risks of publication bias—such as selective reporting of statistically significant coefficients—appear less relevant in our context. Nonetheless, we recognize that some degree of selective reporting cannot be ruled out entirely.

Appendix F. Estimates by Forest Ecological Type

To estimate mean annual forest area growth rates by forest type, data on country-level forest type shares Food and Agriculture Organization of the United Nations (2001), and country-level forest area (in km^2) and annual growth rates World Bank (2023) are used. Country-level forest ecological type shares are multiplied by each country's total forest area in 2016 (the most recent year of our data) to estimate the absolute forest area for each forest type. These area estimates are then used to compute area-weighted means and standard errors of forest area growth rates:

$$\bar{x}_w = \frac{\sum_i w_i x_i}{\sum_i w_i}$$

where x_i is the forest area growth rate in country i, and w_i is the estimated forest area of that type in country i. The weighted variance of each growth estimate is then:

$$\sigma_w^2 = \frac{\sum_i w_i (x_i - \bar{x}_w)^2}{\sum_i w_i}$$

which are converted into standard errors. The resulting growth rates are as in Table 11.

Table 11 Annual forest area growth rates by type

Forest Type	Growth rate (S.E.)
Subtropical	0.44% (0.04%)
Temperate	0.22% (0.03%)
Polar	0.05% (0.00%)
Boreal	0.04% (0.01%)
Tropical	−0.42% (0.03%)
Overall Nontropical	0.18% (0.03%)
Overall	−0.11% (0.04%)

We also perform a check on whether the income elasticity of willingness to pay differs by tropical versus nontropical forest types across our $N = 177$ forest observations. To do so, we add an interaction term $D(\text{Tropical} = 1) \times \log(\text{Income})$ to our forestry estimation model. We find insufficient evidence that the point estimates for nontropical (0.62) and tropical (0.64) forests differ statistically at the 5% level of significance. Subsequently, we compare recommended schedules of increases in public natural capital values, as shown in Fig. 12, under the assumption of a common income elasticity of willingness to pay. Despite using a shared elasticity estimate, differences in nontropical and tropical forest area growth rates (0.18% versus -0.42%) suggest that tropical forests should experience a greater uplift in the values placed on them over time. In comparison to the combined forestry result of a RPC of 1.27% (95-CI: 0.85% to 1.69%), the RPC for nontropical forests relative to consumption goods is estimated as 1.09% (95-CI: 0.66% to 1.50%), and for tropical forests as 1.47% (95-CI: 1.05% to 1.90%), driven by their disparate growth rates.

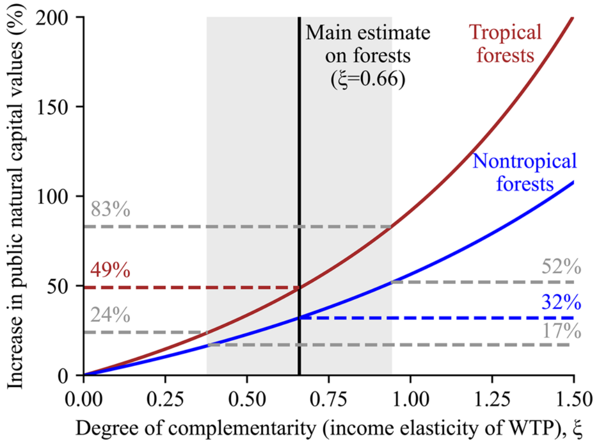

Fig. 12 Sensitivity of forestry results to forest type. *Notes:* Comparison of nontropical and tropical forests under a shared income elasticity of WTP (0.66) but disparate growth rates of 0.18% versus −0.42%, respectively

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10640-025-01042-5.

Acknowledgements We thank Jasper Meya, Sjak Smulders, Daan van Soest and Martin Quaas as well as seminar audiences at BIOECON 2023, the World Bank, idiv Leipzig, MWLR and EAERE 2023 for helpful discussions, and are grateful to Johanna Darmstadt, Mark Lustig and Jasper Röder for excellent research assistance.

Author Contributions Moritz Drupp: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing-Original Draft, Writing-Review & Editing, Visualization, Supervision, Project administration, Funding acquisition. Zachary Turk: Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing-Original Draft, Writing-Review & Editing, Visualization. Ben Groom: Conceptualization, Methodology, Writing-Review & Editing, Funding acquisition. Jonas Heckenhahn: Methodology, Validation, Formal analysis, Investigation, Data Curation, Writing-Review & Editing, Visualization.

Funding Open access funding provided by Swiss Federal Institute of Technology Zurich. We thank Jasper Meya, Sjak Smulders, Daan van Soest and Martin Quaas as well as seminar audiences at BIOECON 2023, the World Bank, idiv Leipzig, MWLR and EAERE 2023 for helpful discussions, and are grateful to Johanna Darmstadt, Mark Lustig and Jasper Röder for excellent research assistance. We gratefully acknowledge funding by the World Bank. M.D. acknowledges support from the German Federal Ministry of Education and Research (BMBF) under grant number 01UT2103B. B.G. acknowledges Dragon Capital for funding the Dragon Capital Chair and funding from the UKRI/NERC BIOADD project (ref: NE/X002292/1). J.H. acknowledges support from the Evangelisches Studienwerk e.V. Villigst. All authors declare that they have no relevant or material financial interests related to the research in this paper.

Data Availability The data and code developed during this research is publicly available in the GitHub repository at https://github.com/zacharyturk/Global_RPC_2025_Drupp_Turk_Groom_Heckenhahn.

Declarations

Ethical Approval No primary data was elicited, thus no ethics statement for human subject research applies.

Conflict of Interest M.D., Z.T., and J.H. had consultancy contracts with the World Bank. All authors declare that they have no relevant or material financial interests related to the research in this manuscript, as the research was conducted open and freely.

References

Adams D, Soto J, Lai J, Escobedo F, Alvarez S, Kibria A (2020) Public preferences and willingness to pay for invasive forest pest prevention programs in urban areas. Forests 11(10):1–16
Al-Assaf AA (2015) Applying contingent valuation to measure the economic value of forest services: a case study in northern Jordan. Int J Sustain Devel World Ecol 22(3):242–250
Arrow KJ, Dasgupta P, Goulder LH, Mumford KJ, and Oleson K (2012) Sustainability and the measurement of wealth. Environ Dev Econ 17(3):317–353
Barbier EB, Czajkowski M, Hanley N (2017) Is the income elasticity of the willingness to pay for pollution control constant? Environ Res Econ 68:663–682
Barrio M, Loureiro ML (2010) A meta-analysis of contingent valuation forest studies. Ecol Econ 69(5):1023–1030
Bastien-Olvera BA, Conte MN, Dong X, Briceno T, Batker D, Emmerling J, Tavoni M, Granella F, Moore FC (2024) Unequal climate impacts on global values of natural capital. Nature 625:722–727
Bastien-Olvera BA, Moore FC (2021) Use and non-use value of nature and the social cost of carbon. Nat Sustain 4(2):101–108
Baumgärtner S, Drupp MA, Meya JN, Munz JM, Quaas MF (2017a) Income inequality and willingness to pay for environmental public goods. J Environ Econ Manage 85:35–61
Baumgärtner S, Drupp MA, Quaas MF (2017b) Subsistence, substitutability and sustainability in consumption. Environ Res Econ 67(1):47–66
Baumgärtner S, Klein AM, Thiel D, Winkler K (2015) Ramsey discounting of ecosystem services. Environ Res Econ 61(2):273–296
Bergstrom JC, Taylor LO (2006) Using meta-analysis for benefits transfer: theory and practice. Ecol Econ 60(2):351–360
Bliem M, Getzner M (2012) Willingness-to-pay for river restoration: differences across time and scenarios. Environ Econ Policy Stud 14(3):241–260
Butchart SH, Walpole M, Collen B, Van Strien A, Scharlemann JP, Almond RE, Baillie JE, Bomhard B, Brown C, Bruno J et al (2010) Global biodiversity: indicators of recent declines. Science 328(5982):1164–1168
Cohen F, Hepburn CJ, Teytelboym A (2019) Is natural capital really substitutable? Annu Rev Environ Resour 44:425–448
Conte MN, Addicott ET, Millerhaller MM (2025) Scarcity, willingness to pay for species, and imperfect substitutability with market goods. J Environ Econ Manage 133:103192
Dasgupta P (2021) The economics of biodiversity and ecosystem services: the dasgupta review
Dogan E, Muhammad I (2019) Willingness to pay for renewable electricity: a contingent valuation study in Turkey. Electr J 32(10)
Drupp MA (2018) Limits to substitution between ecosystem services and manufactured goods and implications for social discounting. Environ Res Econ 69(1):135–158
Drupp MA, Baumgärtner S, Meyer M, Quaas MF, von Wehrden H (2020) Between ostrom and nordhaus: the research landscape of sustainability economics. Ecol Econ 172:106620
Drupp MA, Freeman MC, Groom B, Nesje F (2018) Discounting disentangled. Am Econ J: Econ Policy 10(4):109–134
Drupp MA, Hänsel MC (2021) Relative prices and climate policy: how the scarcity of nonmarket goods drives policy evaluation. Am Econ J: Econ Policy 13(1):168–201
Drupp MA, Hänsel MC, Fenichel EP, Freeman M, Gollier C, Groom B, Heal GM, Howard PH, Millner A, Moore FC, Nesje F, Quaas MF, Smulders S, Sterner T, Traeger C, Venmans F (2024a) Accounting for the increasing benefits from scarce ecosystems. Science 383(6687):1062–1064
Drupp MA, Meya JN, Bos B, Disque S (2024b) Heterogeneous substitutability preferences. *CESifo Working Paper No. 11197*.
Ebert U (2003) Environmental goods and the distribution of income. Environ Res Econ 25(4):435–459

Endalew B, Wondimagegnhu BA, Tassie K (2020) Willingness to pay for church forest conservation: a case study in northwestern Ethiopia. J For Sci 66(3):105–116
Fenichel EP, Abbott JK, Bayham J, Boone W, Haacker EM, Pfeiffer L (2016) Measuring the value of groundwater and other forms of natural capital. Proc Natl Acad Sci 113(9):2382–2387
Food and Agriculture Organization of the United Nations (2001) Global forest resources assessment 2000: main report. FAO Forestry Paper 140, Food and Agriculture Organization of the United Nations, Rome, Italy
Fu S, Viard VB, Zhang P (2021) Air pollution and manufacturing firm productivity: nationwide estimates for China. Econ J 131(640):3241–3273
Gollier C (2010) Ecological discounting. J Econ Theory 145(2):812–829
Groom B, Drupp M, Freeman MC, Nesje F (2022) The future, now: a review of social discounting. Annu Rev Resource Econ 14:467–491
Groom B, Hepburn C (2017) Reflections—looking back at social discounting policy: the influence of papers, presentations, political preconditions, and personalities. Rev Environ Econ Policy 11(2):336–356
Guo D, Wang A, Zhang AT (2020) Pollution exposure and willingness to pay for clean air in urban China. J Environ Manag 261
Hanemann WM (1994) Valuing the environment through contingent valuation. J Econ Perspect 8(4):19–43
Hanley N, Dupuy L, McLaughlin E (2015) Genuine savings and sustainability. J Econ Surv 29(4):779–806
Heal G (2009) Climate economics: a meta-review and some suggestions for future research. Rev Environ Econ Policy 3(1)
Heckenhahn J, Drupp MA (2024) Relative price changes of ecosystem services: evidence from Germany. Environ Res Econ 87:833–880
Hökby S, Söderqvist T (2003) Elasticities of demand and willingness to pay for environmental services in Sweden. Environ Res Econ 26(3):361–383
HM Treasury (2021) Green book supplementary document: environmental discount rate review, conclusion
Hoel M, Sterner T (2007) Discounting and relative prices. Clim Change 84(3):265–280
Huenchuleo C, Barkmann J, Villalobos P (2012) Social psychology predictors for the adoption of soil conservation measures in central Chile. Land Degrad Devel 23(5):483–495
IPBES (2019) Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the intergovernmental science-policy platform on biodiversity and ecosystem services. Technical report, Intergovernmental Platform on Biodiversity and Ecosystem Services
Jacobsen JB, Hanley N (2009) Are there income effects on global willingness to pay for biodiversity conservation? Environ Res Econ 43(2):137–160
Kim J-H, Kim H-J, Yoo S-H (2019) Willingness to pay price premium for smartphones produced using renewable energy. Sustainability 11(6):1566
Kling CL, Phaneuf DJ, Zhao J (2012) From exxon to bp: has some number become better than no number? J Econ Perspect 26(4):3–26
Leung B, Hargreaves AL, Greenberg DA, McGill B, Dornelas M, Freeman R (2020) Clustered versus catastrophic global vertebrate declines. Nature 588(7837):267–271
Lindhjem H, Tuan TL (2012) Valuation of ecosystem services in a green economy: willingness to pay for forest conservation in Vietnam. Environ Econ Policy Stud 14(4):303–323
Liu S, Stern DI (2008) A meta-analysis of contingent valuation studies in coastal and near-shore marine ecosystems. Mar Resour Econ 23(2):119–147
Maharana I, Rai S, Sharma E (2000) Valuing ecotourism in a sacred lake of the sikkim himalaya, India. Environ Conserv 27(3):269–277
Ma T, Min Q, Xu K, Sang W (2021) Resident willingness to pay for ecotourism resources and associated factors in sanjiangyuan national park, China. J Resour And Ecol 12(5):693–706
MEA (2005) Millennium ecosystem assessment. Millennium Ecosystem Assessment
Meyerhoff J, Angeli D, Hartje V (2012) Valuing the benefits of implementing a national strategy on biological diversity—the case of Germany. Environ Sci Policy 23:109–119
Milovantseva N (2016) Are american households willing to pay a premium for greening consumption of information and communication technologies? J Clean Prod 127:282–288
Moeltner K, Rosenberger RS (2014) Cross-context benefit transfer: a bayesian search for information pools. Am J Agric Econ 96(2):469–488
Moore FC, Drupp MA, Rising J, Dietz S, Rudik I, Wagner G (2024) Synthesis of evidence yields high social cost of carbon due to structural model variation and uncertainties. Proc Natl Acad Sci 121(52):e2410733121
Mwebaze P, Marris G, Brown M, MacLeod A, Jones G, Budge G (2018) Measuring public perception and preferences for ecosystem services: a case study of bee pollination in the Uk. Land Use Pol 71:355–362
Neumayer E (2003) Weak versus strong sustainability: exploring the limits of two opposing paradigms. Edward Elgar Publishing

Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD et al (2021) The prisma 2020 statement: an updated guideline for reporting systematic reviews. BMJ 372:n71
Petrolia D, Kim T-G (2009) What are barrier islands worth? estimates of willingness to pay for restoration. Mar Resour Econ 24(2):131–146
Ready RC, Malzubris J, Senkane S (2002) The relationship between environmental values and income in a transition economy: surface water quality in Latvia. Environ Dev Econ 7(1):147–156
Richardson L, Loomis J (2009) The total economic value of threatened, endangered and rare species: an updated meta-analysis. Ecol Econ 68(5):1535–1548
Rouhi Rad M, Adamowicz W, Entem A, Fenichel EP, Lloyd-Smith P (2021) Complementarity (not substitution) between natural and produced capital: evidence from the Panama canal expansion. J Assoc Environ Resour Econ 8(6):1115–1146
Schläpfer F (2008) Contingent valuation: a new perspective. Ecol Econ 64(4):729–740
Schläpfer F, Getzner M (2020) Beyond current guidelines: a proposal for bringing behavioral economics to the design and analysis of stated preference surveys. Ecol Econ 176
Siikamäki J, Piaggio M, da Silva N, Álvarez I, Chu Z (2021) Global assessment of non-wood forest ecosystem services: a revision of a spatially explicit meta-analysis and benefit transfer
Siikamäki J, Santiago-Ávila FJ, Vail P (2015) Global assessment of non-wood forest ecosystem services. Spatially explicit meta-analysis and benefit transfer to improve the world bank's forest weatlh database. 1–97
Skourtos M, Kontogianni A, Harrison P (2010) Reviewing the dynamics of economic values and preferences for ecosystem goods and services. Biodivers Conserv 19(10):2855–2872
Smith VK (2023) Accounting for income inequality in benefit transfers: the importance of the income elasticity of wtp. J Environ Econ Manage 102781
Smulders S (2012) An arrow in the achilles' heel of sustainability and wealth accounting. Environ Dev Econ 17(3):368–372
Smulders S, van Soest D (2023) Natural capital substitution: implications for growth, shadow prices, and natural capital accounting. Mimeo, Tilburg University
Stanley TD, Doucouliagos H (2012) Meta-regression analysis in economics and business. Routledge, Abingdon, UK
Sterner T, Persson UM (2008) An even sterner review: introducing relative prices into the discounting debate. Rev Environ Econ Policy
Subroy V, Gunawardena A, Polyakov M, Pandit R, Pannell DJ (2019) The worth of wildlife: a meta-analysis of global non-market values of threatened species. Ecol Econ 164:106374
Taye FA, Folkersen MV, Fleming CM, Buckwell A, Mackey B, Diwakar K, Le D, Hasan S, Ange CS (2021) The economic values of global forest ecosystem services: a meta-analysis. Ecol Econ 189:107145
Tolunay A, Başsüllü C (2015) Willingness to pay for carbon sequestration and co-benefits of forests in Turkey. Sustainability 7(3):3311–3337
Traeger CP (2011) Sustainability, limited substitutability, and non-constant social discount rates. J Environ Econ Manage 62(2):215–228
Tziakis I, Pachiadakis I, Moraitakis M, Xideas K, Theologis G, Tsagarakis K (2009) Valuing benefits from wastewater treatment and reuse using contingent valuation methodology. Desalination 237(1–3):117–125
Weikard H-P, Zhu X (2005) Discounting and environmental quality: when should dual rates be used? Econ Model 22(5):868–878
World Bank (2023) Forest area (sq. km) [indicator ag.lnd.frst.k2]. World Development Indicators database. Accessed July 2023
World Bank T (2021) The changing wealth of nations 2021: managing assets for the future. The World Bank
Yang J, Zou L, Lin T, Wu Y, Wang H (2014) Public willingness to pay for co2 mitigation and the determinants under climate change: a case study of suzhou, China. J Environ Manag 146:1–8
Zhu X, Smulders S, de Zeeuw A (2019) Discounting in the presence of scarce ecosystem services. J Environ Econ Manage 98:102–272