Environmental Research Letters

TOPICAL REVIEW • OPEN ACCESS

Are biodiversity losses valued differently when they are caused by human activities? A meta-analysis of the non-use valuation literature

To cite this article: Anne Nobel *et al* 2020 *Environ. Res. Lett.* **15** 073003

Environmental Research Letters

TOPICAL REVIEW

CrossMark

OPEN ACCESS

RECEIVED
27 December 2018

REVISED
17 April 2020

ACCEPTED FOR PUBLICATION
30 April 2020

PUBLISHED
9 July 2020

Are biodiversity losses valued differently when they are caused by human activities? A meta-analysis of the non-use valuation literature

Anne Nobel[1,7], Sebastien Lizin[1], Roy Brouwer[2,6], Stephan B Bruns[1,3], David I Stern[4] and Robert Malina[1,5]

1 Centre for Environmental Sciences, Hasselt University, Martelarenlaan 42, 3500, Hasselt, Belgium
2 Department of Economics and the Water Institute, University of Waterloo, 200 University Avenue West, Ontario, Canada
3 Department of Economics, University of Göttingen, Humboldtallee 3, 37073, Göttingen, Germany
4 Crawford School of Public Policy, The Australian National University, 132 Lennox Crossing, Acton, ACT 2601, Australia
5 Laboratory for Aviation and the Environment, Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, United States of America
6 Department of Environmental Economics, Institute for Environmental Studies, Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV, Amsterdam, The Netherlands
7 Author to whom any correspondence should be addressed

E-mail: anne.nobel@uhasselt.be

Keywords: biodiversity, non-use values, willingness-to-pay, climate change, meta-analysis

Supplementary material for this article is available online

Abstract

Many countries committed to climate action by adopting the Paris Agreement and Sustainable Development Goals in 2015. This study synthesizes 40 years of scientific evidence of what may be an important benefit of these commitments: the non-use value of biodiversity conservation. The synthesis investigates whether biodiversity values can be integrated into climate change damage estimates based on non-use valuation studies of different threats to biodiversity. In the absence of estimates of public willingness to pay (WTP) to avoid the adverse impacts of anthropogenic climate change on biodiversity, we synthesize non-use values for biodiversity conservation from stated preference studies that account for a heterogeneous set of biodiversity threats. We test whether biodiversity non-use values are affected by the threats that policies aim to address, be it human activities or other threats. We estimate meta-regression models in which we explain the variation in these non-use values by accounting for the observed heterogeneity in good, methodology, sample, and context characteristics. We estimate meta-regression models using 159 observations from 62 publications. The models suggest that non-use values for biodiversity conservation addressing human impacts may be larger than those addressing other threats. We also find that non-use values are generally not sensitive to which biodiversity indicators, habitat types, or taxonomic groups are valued. We predict that the mean annual WTP for avoiding human-caused biodiversity losses ranges from 0.2 to 0.4% of GDP per capita. Our findings suggest that state-of-the-art climate change damage functions in integrated assessment models may underestimate actual damage costs because they do not incorporate the premium that the public is willing to pay to avoid human-caused biodiversity losses.

1. Introduction

1.1. The importance of biodiversity values in climate change policy analysis

Concerns that climate change caused by anthropogenic greenhouse gas emissions is becoming a major driver of biodiversity losses (IPCC 2014, 2018, 2019) have increasingly led decision-makers to consider emission reduction policies that avoid these losses (Warren *et al* 2001, Kerr and Packer 2015, Newbold and Newbold 2018). The Sustainable Development Goals (SDGs) that were adopted in 2015 stipulate, among other things, that the international community should 'take urgent action in response to climate change and its impacts' (SDG 13) and 'halt biodiversity loss' (SDG 15). Furthermore, the ratification of the Paris Agreement in the same year, which had the aim to 'strengthen the global response to the threat of climate change', shows that there is broad international support for the notion that climate action and biodiversity conservation are paramount in order to limit the impacts of ongoing human activities. With limited resources available and the need for substantial investment between now and 2030 to achieve the climate goals of the Paris Agreement and SDGs (United Nations 2019), policymakers must consider both the costs and benefits of alternative climate mitigation policies.

Biodiversity, which can be defined as the diversity and variability in nature (Delong 1996), brings a variety of benefits. According to the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES, Díaz *et al* 2015), these benefits can be divided into intrinsic and instrumental values. Intrinsic values reflect the worth and importance of biodiversity, independent of human considerations. Instrumental values reflect the benefits of biodiversity conservation to society. While the IPBES framework allows for various ways of conceptualizing and measuring biodiversity values, the instrumental value of biodiversity is often quantified by eliciting monetary values in hypothetical markets. The resulting monetary value estimates are useful because they enable the inclusion of environmental impacts into cost-benefit analyses of conservation policy (Nunes and Van den Bergh 2001). Furthermore, monetary valuations help to communicate the value of biodiversity to policymakers and the general public (Díaz *et al* 2015).

Instrumental values can be divided into use and non-use values. Use values reflect the benefits from using or consuming biodiversity, for example by extracting biological resources or recreation in biodiverse areas. Non-use values are the benefits that people derive from the knowledge that biodiversity will continue to exist and will be preserved for others, including future generations, without ever using it (Krutilla 1967, Arrow *et al* 1993). Non-use values are an important component of the total economic value of biodiversity conservation (Pearce and Turner 1990) and may therefore also be an important economic benefit of policies that reduce biodiversity losses due to climate change. However, economic impacts of biodiversity losses that have received most attention are primarily related to use values, such as reduced food production (see, e.g. IPCC 2014), whereas much less effort has been made to include empirical evidence of biodiversity non-use values into the evaluation of climate change policy.

1.2. Current approaches to including biodiversity values in climate change policy analysis

The economic benefits of climate change mitigation policies, such as emission taxes or renewable energy subsidies, are typically expressed in terms of avoided economic damages; *in casu* the Social Cost of Carbon (SCC), which 'represents the economic cost caused by an additional ton of carbon dioxide emissions or its equivalent' (Nordhaus 2016, p 1518). The SCC is an aggregation of estimates of worldwide damages across several categories, such as agricultural productivity, human health, and damages from global mean sea-level rise, and is typically estimated through integrated assessment models (IAMs) that model climate change and the global economy jointly.

These IAMs rely on an applied general equilibrium representation of an individual household that maximizes utility as a function of consumption, greenhouse gas abatement costs and climate damages (Howard and Sterner 2014). IAMs are used to predict economic damages due to global warming. Based on a range of results from different climate IAMs, the (IPCC 2014) predicted that a global temperature increase of 2.5 degrees Celsius above pre-industrial levels would cause annual economic damages of between 0.2 and 2.0% of global GDP. However, these damage cost estimates contain arbitrarily fixed values for ecosystem and species losses. From among the three IAMs most widely used to inform climate change policy (Bonen *et al* 2014), two models (the DICE and FUND models) assume an arbitrary annual willingness to pay of 0.1% of GDP for the total economic value of preventing ecosystem loss (Nordhaus and Boyer 2000) or species loss (Anthoff and Tol 2013). Nordhaus and Boyer (2000, p. 86) stated that this assumption is based on an annual willingness-to-pay of 1% of the annualized capital value of ecosystems, but provided no further empirical evidence to support this assumption. Alternatively, the model documentation of FUND refers to (Pearce and Moran 1994), who summarized evidence on the economic value of biodiversity, although it is again unclear which estimate was selected. The third model (the PAGE model) assumes a mean annual WTP of 0.5% of global income to avoid a range of 'non-economic impacts' (Hope 2012), meaning it is not possible to determine which fraction of damages is attributable to biodiversity damages in this model (Brooks and Newbold 2014). In sum, the extent to which the assumptions adopted in these models are in agreement with empirical evidence of the economic value of biodiversity is unclear.

Some recent studies have proposed a more careful integration of biodiversity values into existing IAMs by proposing the addition of a biodiversity value term directly into the utility function of the representative individual household (e.g. Brooks and Newbold 2014, Kaushal and Navrud 2018). The parameters of this biodiversity value term are calibrated based on (1) the predicted biodiversity losses as a result of a global increase in temperature, and (2) stated preference studies that elicit monetary value changes as a consequence of biodiversity changes, which are caused by one or a set of drivers. While biodiversity changes are presented as hypothetical scenarios to the survey respondents in these studies, they are not actually observed or experienced. Importantly, different primary valuation studies investigated monetary values for different threats to biodiversity. The monetary values elicited by stated preference studies are sensitive to the information set provided to survey participants (Czajkowski *et al* 2016). This implies that the same biodiversity change can be valued differently, depending on the nature of the described cause of the biodiversity change. The impact of the nature of the cause on non-use values remains unexplored and is therefore not considered in state-of-the-art biodiversity value functions. This may be problematic, because if inaccurate biodiversity non-use values are included into climate change damage estimates, which are then used to evaluate climate change policy options, this could lead to biased policy recommendations.

1.3. The relevance of the perceived threat to biodiversity

Stated preference methods are grounded in economic value theory, which interprets value as the utility that humans obtain from environmental changes, or changes in the characteristics of environmental goods (Lancaster 1966). Standard economic theory assumes that people's preferences are based on the utility they expect from these environmental outcomes (Bulte *et al* 2005). However, a contrasting view is that people's stated preferences may not depend solely on outcomes; rather, stated preferences for changes in the provision of public goods[1] may vary with information provided to respondents about what drives these changes, even if the outcomes are the same (Homer and Kahle 1988, Stern *et al* 1999, Ajzen 2005). Specifically, several authors have suggested that user preferences (Kahneman *et al* 1993, Kahnemann and Ritov 1994) and non-user preferences (Bulte *et al* 2005) depend on the perception of whether the changes in public goods are due to human activities. Those authors have shown empirically that individuals are willing to pay more to undo harm to public goods when they are informed that the harm was anthropogenic than when it constituted a natural change. Hence, they conclude that people's preferences related to a change in public goods can be affected by whether the policy aims to reduce human influence on these goods, and do not depend solely on outcomes only. When the implications of these findings are extended to non-use values of biodiversity conservation, non-use values may vary depending on whether a policy intends to reduce human influence on biodiversity. Specifically, this means that people may hold higher non-use values for a policy that addresses human-caused biodiversity losses. Examples of such policies are restricting resource extraction in protected areas, reducing the risk of oil spills or arson. On the other hand, non-use values may be lower for policies that address threats that people do not perceive as being linked with human activities. If non-use values for biodiversity conservation policies vary with this perception, this implies that the biodiversity component of cost estimates of anthropogenic greenhouse gas emissions, which climate mitigation policies aim to reduce, may be inaccurate if it is based on valuations of biodiversity losses due to non-human threats. While different primary studies used for the development of biodiversity value functions focus on different causes (such as pollution from nearby agricultural activities, oil spills, and drought-induced wildfires), no studies to date have explicitly focused on anthropogenic climate change as a driver of biodiversity loss. However, it is unclear whether it is appropriate to integrate biodiversity values into climate change damage estimates based on different studies with different threats to biodiversity. In the absence of any non-use valuation studies that deal specifically with anthropogenic climate change impacts on biodiversity, we test the hypothesis that the non-use value of biodiversity is dependent on whether a threat is perceived as human-made or not for a broader set of threats; that is, any threats that are accounted for in the relevant non-use valuation studies.

1.4. Contribution of this paper

Our study contributes to the literature in two relevant ways. First, we prepare a meta-regression analysis of non-use values of biodiversity conservation. We try to assess whether non-use values of biodiversity conservation are significantly impacted by the origin of the biodiversity threat articulated in the primary study. More specifically, we assess the monetary valuation impact of presenting a biodiversity threat as *human-caused*, by adding the presence (or absence) of this information as a covariate in several meta-regression models. No previous meta-analyses have explored the potential relevance of the presence of this information on the stated values of biodiversity conservation (e.g. Martín-López *et al* 2008, Richardson and Loomis 2009, Jacobsen and Hanley 2009, Ojea and Loureiro 2011, Hjerpe *et al* 2015). Second, we provide an updated, comprehensive synthesis of non-use values that includes both contingent valuation (CV) and choice experiments (CE). The number of published CEs has increased considerably over the past two decades, and now exceeds the number of published CV studies (Mahieu *et al* 2014, Johnston *et al* 2017). All of the above-mentioned studies have focused on the total economic value of biodiversity conservation, including use values, except (Jacobsen and Hanley 2009), who focused on non-use values

[1] Many environmental goods are considered public goods (Loomis 1996).

(willingness-to-pay OR wtp OR stated AND preference* OR "contingent valuation" OR "choice experiment") AND ("non-use" OR bequest OR existence OR altruisti* OR "passive use") AND (biodiversity OR species OR mammal OR bird OR fish OR reptile OR vertebrate OR habitat* OR ecosystem* OR protected AND area* OR reserve OR conservation AND area* OR natural AND area* OR national AND park OR forest* OR wood* OR mountain* OR dry* OR shrub* OR scrub* OR grass* OR wet* OR lake* OR water OR marine OR coast* OR beach OR mangrove OR lagoon OR reef) AND (conservation OR preservation OR restoration OR protection OR “climate adaptation”)

Figure 1. Search query (formatted for Scopus).

of biodiversity conservation only from CV studies. As (Brooks and Newbold 2014) showed, biodiversity losses can be included in climate change damage assessments by adding a biodiversity value component into the utility function of a representative individual household, which is then calibrated based on economic valuation studies in which non-use values are estimated empirically. They also noted that this is only possible if the estimates from these economic valuation studies reflect pure non-use values because (consumptive-) use values stemming from the provisioning services of biodiversity are already reflected in the consumption part of the utility function. However, previous studies that proposed a biodiversity component are based on primary studies that did not separate non-use values from use values (e.g. Brooks and Newbold 2014, Kaushal and Navrud 2018). Hence, the present study is the first to provide a basis for a biodiversity value function that is consistent with economic theory by only including primary studies that specifically estimated non-use values. As noted above, the non-use valuation literature does not explicitly account for anthropogenic climate change as a threat to biodiversity. However, controlling for human causes within biodiversity value functions may provide a first step towards more accurate monetary estimates of non-use values that can be included in climate change damage assessments.

The remainder of this paper is organized as follows. Section 2 introduces the theoretical framework for estimating non-use values in monetary terms. Section 3 discusses the data collection and screening procedures, as well as the meta-regression model specification. Section 4 presents both a discussion of the empirical results of the meta-regression analysis as well as an assessment of the robustness of our findings. Finally, section 5 provides some conclusions and limitations of this review, plus avenues for future research.

2. Theoretical framework

The estimation of non-use values in monetary terms is grounded in economic value theory (Lancaster 1966, Bergstrom and Taylor 2006). This theory is based on the proposition that the utility that individuals obtain from environmental changes can be expressed in monetary terms by estimating the change in income necessary to fully offset the positive utility obtained from improvements of environmental goods; or, conversely, by estimating the change in income necessary to create an equal amount of disutility caused by a deterioration of environmental goods (Whitehead *et al* 2011). This amount of income is referred to as the willingness-to-pay (WTP) and can be expressed formally as (Bergstrom and Taylor 2006):

$$WTP_i = f_i\left(P_i, H_i, Q_i^* - Q_i, C_i^* - C_i, I_i\right) \quad (1)$$

where the WTP of individual i depends on the prices of market goods (P_i) faced by the individual, characteristics of the household to which individual i belongs (H_i), the quantity of environmental goods (Q_i), the quality of environmental goods (C_i), and the information (I_i) available to individual i. Furthermore, Q_i^* and C_i^* represent the quality and quantity of environmental goods in an alternative state of the world. In this study, the difference between the alternative state of the world (Q_i^* and C_i^*) and the current state of the world (Q_i and C_i) represents the change in the quality and quantity of biodiversity as defined by the primary studies. Equation (1) provides the theoretical framework for a meta-regression analysis of WTP values for biodiversity changes, while the right-hand side of equation (1) can be extended with additional variables that are hypothesized to influence WTP values.

3. Methods

3.1. Study selection and screening

The data used to inform our analysis were collected from January through March 2019. We searched for non-use valuation studies that focused on the conservation or restoration of habitats, species, or both. We included both CV studies and CEs. We considered papers published in peer-reviewed journals, as well as unpublished working papers, government reports, technical reports and dissertations. The search query is presented in figure 1.

We limited the search queries to only include studies written in English, but we did not impose geographical or temporal restrictions. We performed

Table 1. Descriptive statistics of the WTP estimates included in the meta-database (N = 159).

	N	Simple mean	Weighted mean WTP	Truncated weighted mean	Std. dev.	Min.	Max.
Study type							
Contingent valuation	124	125.7	234.3	64.4	234.0	2.3	1419.4
Choice experiments	35	122.1	147.1	103.0	124.1	1.3	676.4
Biodiversity indicator							
Habitat quality	110	146.5	571.3	172.4	250.6	2.3	1419.4
Species abundance	32	55.6	131.7	131.7	66.1	1.3	385.5
Species richness[2]	17	115.6	150.6	150.6	65.5	11.5	209.6
Habitat type or species affected							
Forest habitat	58	201.9	381.6	71.1	321.7	2.6	1419.4
Marine habitat	37	76.0	76.3	79.9	56.8	11.4	239.9
Wetland habitat	29	119.8	188.6	46.7	131.8	5.2	676.4
Grassland or shrubland habitat	3	27.6	45.0	71.7	43.0	2.3	77.3
Bird species	18	55.6	66.6	66.6	66.1	1.3	385.5
Mammal species	10	37.5	55.2	55.2	27.2	1.3	89.4
Other species	6	105.1	256.9	256.9	138.4	30.6	385.5
Welfare measure							
Recover or improve biodiversity	65	108.5	131.2	99.7	116.5	1.3	676.4
Prevent biodiversity loss	94	136.2	262.7	69.3	261.5	2.3	1419.4
Payment schedule							
Annual payments	125	118.3	211.9	82.4	229.8	1.3	1419.4
One-off payments	34	149.0	181.3	118.4	143.7	12.8	676.4
Literature type							
Peer-reviewed literature	152	128.9	212.6	91.9	218.2	1.3	1419.4
Grey literature	7	38.6	27.7	27.7	38.4	7.7	115.9
Conservation policy							
Reduces negative impact from human activities only	140	134.0	229.8	78.7	220.2	1.3	1419.4
Agricultural activities	32	280.5	471.5	70.4	406.0	11.5	1419.4
Several human activities (e.g. recreation, hydropower, human encroachment)	30	59.3	71.2	79.7	46.8	5.2	220.8
Fishing activities	29	62.1	63.3	63.3	50.7	15.1	239.9
Water pollution from nearby economic activity	13	129.4	158.1	158.1	62.7	44.1	209.6
'Human activities' in general	11	172.2	186.6	186.6	112.7	1.3	399.9
Mining activities	9	45.5	46.2	46.2	24.8	11.4	75.6
Urban development	8	154.0	134.1	134.1	113.3	28.7	376.1
Oil spills	4	81.8	138.8	138.8	14.8	70.1	103.6
Habitat loss due to land use change	4	21.0	20.9	20.9	29.1	4.0	64.6
Reduces negative impact from human activities and other threats	2	407.5	608.3	138.5	774.6	138.5	1234.0
Human caused and drought induced wildfires	1	138.5	138.5	138.5	0.0	138.5	138.5
Sea-level rise, subsidence, erosion, saltwater intrusion, human development	1	676.4	676.4	N/A	0.0	676.4	676.4
Reduces negative impact from other threats only	17	16.4	15.2	15.2	11.5	2.3	40.8
Drought-induced wildfires	1	12.8	12.8	12.8	0.0	12.8	12.8
Hurricanes	6	13.7	13.7	13.7	2.9	10.7	18.8
Saline tidal water	1	25.2	25.2	25.2	0.0	25.2	25.2
Disease outbreaks	9	17.5	21.1	22.1	13.8	2.3	40.7
Continent							
North America	72	173.7	309.2	62.1	300.1	4.0	1419.4
South America	2	25.8	25.8	25.8	20.4	11.4	40.2
Europe	62	92.8	100.4	100.4	82.2	1.3	399.9
Asia	18	43.8	44.7	44.7	22.7	12.8	81.8
Oceania	5	151.8	123.5	123.5	125.2	35.6	334.9

[2]The authors of one study stated that the respondents valued species diversity (Börger and Hattam 2017). However, the description of biodiversity implies that the authors interpreted species diversity as the number of different species in the area. Hence, we categorized this study under species richness.

Notes: Standard deviations, minima and maxima are based on the full, unweighted sample. Weighted mean is calculated with weights based on the number of respondents per estimate. The truncated weighted mean excludes eight outliers.

the initial search query (see table 1) in Scopus using the institutional subscription of the Hasselt University Library. We also searched Web of Science, JSTOR, RePeC, OATD.org, as well as three

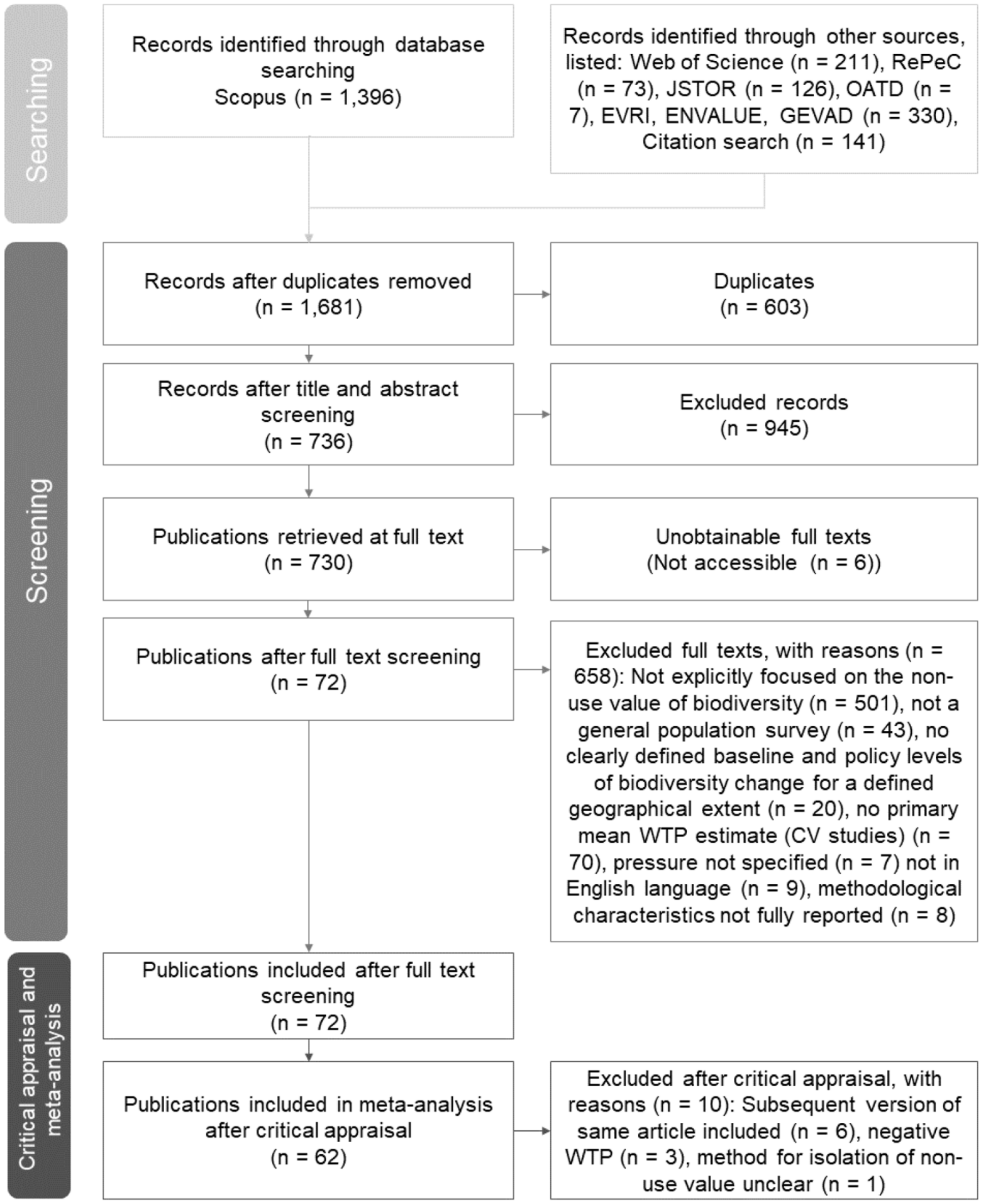

Figure 2. Flow diagram of systematic review (adapted from Haddaway *et al* 2017).

valuation databases (EVRI, ENVALUE, and GEVAD). Furthermore, we scanned the reference lists of five previously conducted meta-analyses related to biodiversity conservation (Martín-López *et al* 2008, Jacobsen and Hanley 2009, Richardson and Loomis 2009, Ojea and Loureiro 2011, Hjerpe *et al* 2015) and scanned the reference lists of the studies that passed the initial screening based on title and abstract. This led to a database of 1681 potentially relevant publications, after removing duplicates. The review procedure is visually represented in figure 2.

During the screening of the studies,[3] we considered estimates of CV studies to be eligible for inclusion only if (1) the author explicitly stated that the estimate consists mainly or exclusively of non-use values for biodiversity conservation, (2) respondents indicated which part of their total economic

[3]The list of potentially eligible studies included several publications authored by co-authors of this review (SL and RB). To ensure the objectivity of the screening process, these co-authors were not involved in any eligibility decisions or consistency checks regarding these specific publications.

value represents non-use value, or (3) respondents indicated that they had not used or would not use the environmental good in question. From the retrieved CEs, we considered studies to be eligible only if (1) they included one or more biodiversity related indicators, such as habitat size or species richness, for which the authors explicitly stated that the marginal utility of these indicators reflects non-use value, or (2) respondents indicated they had not used the environmental good during a previous historical period or did not anticipate any future use. Furthermore, studies were only included if they provided sufficiently detailed information about the environmental good, methodology and sample, such as a description of the biodiversity change scenario (for CV studies); a specification of the status quo and policy levels of the biodiversity indicator so that the biodiversity change caused by the policy response could be derived (for CEs); an explicit description of which threats to biodiversity are addressed by the proposed policy; a quantitative or qualitative description of the scope of the policy response, the sample, the sample size, and the payment vehicle and timing of the payments. We only included WTP estimates from studies that did not target specific user groups. Consequently, studies targeting groups such as national park visitors, farmers, or landowners were excluded. All authors of this paper performed consistency checks for randomly selected records for each stage of the reviewing process; that is, for eligibility decisions based on title and abstract (50 records) and for eligibility decisions based on full text (14 excluded records were checked for rightful exclusion, and seven included records were checked for rightful inclusion and study validity). Furthermore, several studies included in the final database were checked for consistent and accurate data entry and coding. These consistency checks did not lead to unresolved disagreements. However, one of the authors identified two studies that were considered based on the full text but could have been excluded based on title and abstract.

3.2. Database development

3.2.1. Response variable.

In all studies, non-use values are measured in terms of public WTP for biodiversity improvements or public WTP to avoid biodiversity loss. In the case of CV studies, the most commonly reported effect sizes are estimates of the mean WTP for hypothetical policy scenarios. These policy scenarios are indivisible in that they represent an integrated set of changes of an environmental good (Johnston *et al* 2017). These estimates can be directly entered into the database, because mean WTP is the key variable of interest in our theoretical framework. However, CEs often only report the marginal WTP values associated with one level increase of particular attributes of an environmental good. Since policy scenarios can be of a larger scope and magnitude—that is, policy scenarios can lead to changes of multiple attributes and these changes can cover multiple levels—a necessary step for including CEs in the regression analysis is to convert marginal values to mean WTP values. Mean WTP values can be approximated using the following equation (Hensher, Rose, and Greene, 2005):

$$E(WTP) = -\frac{1}{\beta_m}\left[\ln\left(\sum_{a=1}^{A} e^{\sum \beta_\alpha X_\alpha^0}\right) - \ln\left(\sum_{a=1}^{A} e^{\sum \beta_\alpha X_\alpha^1}\right)\right] \quad (2)$$

where β_m denotes the marginal utility of income, β_a denotes the marginal utility of a one-level increase of attributes a, and X_a^0 and X_a^1 denote the status quo and policy levels of these attributes, respectively. We assumed in our analysis that the biodiversity-related indicators increase from their status quo levels to the levels that the primary study defined as the maximum level of biodiversity conservation; that is, the largest improvement level or the largest avoided loss. The other attributes are assumed to remain at status quo levels, effectively dropping out of equation (2). Some CEs include an alternative-specific constant that accounts for the utility that individuals derive from remaining in the status quo or changing to a policy scenario. We include this constant in the calculation of the utility changes induced by policy scenarios.

If more than one publication of the same CV study or CE passed the screening, and the publications valued the same environmental good using the same methodology and sample, we only entered estimates from the most recent version into our database. We excluded three publications, two of which are based on the same data (Kaffashi *et al* 2012, 2013, Scott 2018), that reported negative mean WTP values for biodiversity conservation. Negative WTP values are likely to be the result of the unintended measurement of the perception of specific resource user groups whose interests conflicted with conservation. Specifically, in the first study (Kaffashi *et al* 2012, 2013), the sample was taken near to the environmental good while the description of the biodiversity indicator emphasizes that diverse human activities will be forbidden. In the second study (Scott 2018), the biodiversity indicator implies that more biodiversity will be realized at the expense of quinoa production, which the primary author considers important for the population from which the sample was taken. We also excluded one study that did not report the method used to separate non-use values from use values. Table A1 in appendix A shows the full list of included studies.

All monetary values obtained from the primary studies are converted into 2017 purchasing-power-parity-adjusted US Dollars (World Bank 2019). For studies that reported multiple estimates (as part of a sensitivity analysis, for example), we extracted multiple estimates only if at least one of the explanatory variables varied between these estimates.

If variation between multiple estimates from the same study could not be attributed to changes in any of the explanatory variables, we extracted the most accurate estimate based on (in decreasing order of importance): (1) the smallest standard error (if reported), (2) the largest sample size (if different across mean WTP estimates), or (3) the relative model fit based on information criteria. This resulted in a total of 159 data points.

3.2.2. Explanatory variables.
In order to explain heterogeneity in the estimated WTP values due to varying characteristics of the environmental good, we included several variables. First, economic valuation studies operationalize biodiversity in various ways. (Nunes and Van den Bergh 2001) pointed out that most economic valuation studies that claim to value biodiversity do not clearly define biodiversity, but rather focus on policies that are intended to preserve individual habitats or species. Consequently, these studies actually value biological resources instead of biological diversity from an ecological perspective. Since the conservation of habitats is a necessary condition for biodiversity conservation in the long run (United Nations 1992),[4] it may be argued that such policies contribute to biodiversity conservation, although the linkage between the particular habitats or species and biodiversity remains implicit. To explore whether the definition of biodiversity affects WTP values, we distinguish between three definitions typically employed in economic valuation studies (Nunes and Van den Bergh 2001). The first indicator is habitat quality. This is the broadest definition and does not indicate which particular biodiversity aspect will be affected within a habitat and to what extent. The second indicator is the number of individuals of a particular species in a particular area, or species abundance. The third indicator is the number of species within a particular area, or species richness (Hamilton 2005). We do not account for the quantitative change of biodiversity in terms of these biodiversity indicators, because this information is typically not provided by non-use valuation studies.

Second, different studies focus on different habitats or species. We included dummy variables for whether the proposed policy targets a particular habitat type based on the (IUCN 2019) habitat classification scheme, or targets particular species within a taxonomic group. For the taxonomic groups we differentiated between mammals, birds and other taxa based on (Czech *et al.* 1998), who found that people value mammals, birds, and plants more highly than they value invertebrates, fish, reptiles, amphibians, and micro-organisms.

We included a dummy variable for whether the welfare estimate measures public WTP for a recovery or improvement of biodiversity—that is, a compensating surplus instead of an equivalent surplus (baseline: avoiding a loss) (Lindhjem 2007). Contrary to the assumptions in standard economic theory, respondents may value preventing a loss more highly than a same-sized gain (Tversky and Kahneman 1991). Furthermore, we included a dummy variable that reflects whether WTP values come from studies that express biodiversity changes in terms of probabilities. These WTP values may be different from WTP values for biodiversity changes without any uncertainty, because respondents may make their own risk judgment or because they are risk-averse (Lundhede *et al* 2016). This variable assumes the value '1' if the characteristics of the environmental good are uncertain in either the baseline scenario, the policy scenario, or both, and '0' otherwise.[5]

In order to test the effect of providing information about the threat to biodiversity, we include a dummy variable that reflects whether the proposed policy in the primary study is intended to reduce negative impacts from explicitly mentioned human activities on biodiversity. For each original paper, we determine whether the negative impacts addressed by the proposed policies are linked with human activities according to the information set provided to survey participants. This means that our meta-analysis is based on the assumption that survey participants gave their responses in light of the information provided to them. However, we cannot control for the fact that some participants may possess other knowledge or hold different beliefs regarding the causes, or even underlying causes, of biodiversity change. Examples of human threats include timber harvesting, water pollution, oil spills and arson, whereas examples of other—non-human—threats include saline tidal water, drought-induced wildfires, and insect outbreaks.[6] This distinction leads to a classification challenge, because some studies provide descriptions of biodiversity policies that address both human and other threats. Since the distinction between human and other threats may affect the outcome of the test

[4]These studies implicitly assume that the conservation of biological resources is a *sufficient* condition for biodiversity conservation, as well.

[5]Economic values obtained with stated preference methods are based on the assumption that the actual impact of proposed policies is equal to the intended hypothetical change from a baseline situation to a hypothetical target situation as it was defined in the survey; that is, policy outcomes are exactly as expected.

[6]We are aware that the increased frequency and intensity of some biodiversity disturbances, such as wildfires or insect outbreaks, may be attributed to both human activities and other threats (Kurz *et al* 2008, Allen *et al* 2010, Waring *et al* 2011), and that some disturbances may have both negative and positive effects on biodiversity. In this study, we assume that respondents gave their responses in the light of the information they were provided with. This means that we considered biodiversity losses to be human-caused if the primary study mentioned that the policy reduces negative impacts from human activities, and all pressures are assumed to have a negative effect on biodiversity.

of the main hypothesis in this paper, we applied two different classification approaches. The first approach is less strict in its definition of human threats because it codes a conservation policy as aimed at reducing human threats (that is, it takes the value '1') if the policy description addresses at least one human threat. This variant of 'human threat' will be included in a first meta-regression model (Model I). The second approach is stricter because it codes a conservation policy as aimed at reducing human threats (that is, it takes the value '1', and '0' otherwise) if and only if all negative impacts addressed by the policy description are human-caused. This variant will be included in a second meta-regression model (Model II). All other explanatory variables are identical across these two models.

Regarding the methodological characteristics, we included dummy variables for whether the responses were elicited in a face-to-face interview (baseline: mail or phone survey) (Loureiro and Lotade 2005); whether the payment is a recurring, annual payment (baseline: one-off payment)[7] (Stevens et al 1997); whether the payment is voluntary (such as a donation) (baseline: mandatory payment, such as taxes, levies) (Champ et al 2002); and whether respondents are asked to make a payment decision on behalf of their household (baseline: respondents make an individual payment decision) (Ojea and Loureiro 2011). We also included a dummy variable for whether protest responses were removed from the sample, as removing some of the zero-WTP responses is expected to have a positive effect on WTP estimates. Furthermore, we accounted for whether the study applies the CE methodology (baseline: CV), since WTP estimates from CEs are expected to differ from CV studies (e.g. Boyle et al 2004, Brouwer et al 2017). Furthermore, for CV studies we included a dummy variable to indicate whether values are elicited through an open-ended or payment card format (baseline: dichotomous choice format) (Bateman and Jones 2003). For various reasons, including respondent preference uncertainty, open-ended WTP questions may either yield higher or lower values (Johnston et al 2017). Since WTP estimates are sensitive to distributional assumptions (Borzykowski et al 2018), we also included a dummy variable to indicate whether estimates from CEs were obtained using mixed logistic regression, including random parameter estimates, for the choice attributes (baseline: conditional logistic regression). Analogously, for CV studies, we included a dummy variable for non-parametric WTP estimates (baseline: parametric estimate).

For the sample characteristics, we included the study year to account for general improvements in stated preference methods. We also accounted for the potential influence of the method by which non-use values were estimated (Johnston et al 2005). There are several methods for estimating non-use values. First, respondents can be asked to indicate which portion of their total economic value is motivated by non-use considerations. This method has been criticized because of the cognitive difficulties involved (Mitchell and Carson 1989). We included a separate dummy variable to account for the application of this 'apportioning' method. Second, non-use values can be estimated by separating non-users from users based on whether they visited the resource in the past, or whether they anticipate any visits in the future (Johnston et al 2005). This method may underestimate non-use values across users and non-users, because non-users may express lower non-use values than users due to their lack of knowledge about the environmental good (Johnston et al 2003; Whitehead and Blomquist 1991a, 1991b). We included a dummy variable for the 'non-user' method to account for this potential effect. The reference category for the 'non-user' and 'apportioning' categories are studies that assumed that stated values are mainly or only non-use motivated, often because the environmental good is remotely located or has little use value. In some of these studies, respondents are also reminded that they would not be able to visit the environmental good. However, the number of these studies is too small for it to be included as a separate subcategory. [8] Our prior expectation is that the 'non-user method' has a negative effect on WTP values. We have no prior expectation about the effect of the 'apportioning' method.

We also included two additional context characteristics. First, we included the gross domestic product (GDP) per capita in the study year (converted to purchasing-power-parity-adjusted USD 2017), because income growth may be a significant determinant underlying WTP for environmental change reflecting ability to pay (Jacobsen and Hanley 2009). Second, we included a dummy variable that reflects whether the primary study data were collected in North America (baseline: rest of the world) (Ojea and Loureiro 2011).

Finally, we tested whether the peer-reviewed literature provides higher estimates than the grey literature (Model III). This is tested by adding a dummy variable to Model I, which takes on the value '1' for peer-reviewed publications, and '0' otherwise.

3.3. Meta-regression model

The meta-regression analysis is guided by the following general regression equation:

$$\log\left(y_{jt}\right) = \alpha + \beta x_j + \boldsymbol{\gamma} \mathbf{z}_{jt} + \varepsilon_{jt} \qquad (3)$$

[7]Mean WTP values are converted to annual values in the case of recurring payments with intervals other than annual payments.

[8]Yet another method is to calculate non-use value components from total value and direct use values (Johnston et al 2003). We did not find any applications of this method in our meta-database.

in which y_{jt} is the predicted mean WTP for study j with treatment t; α is an unknown parameter; x_{jt} is a dummy variable that takes the value '1' if the conservation policy in study j addresses human threats and '0' otherwise and β is the corresponding unknown parameter. All other explanatory variables are aggregated in vector $\mathbf{z}_{jt}$, and γ is a corresponding vector with unknown parameters; and ε_{jt} is the error term. We opt for a logarithmic transformation of WTP and GDP because the distribution of WTP values is expected to be skewed. The log transformation is expected to improve model fit and the advantage of the double-log functional form is that it allows us to directly estimate the income elasticity of WTP. This functional form is common in the environmental and resource economics literature (Nelson and Kennedy 2009).

The econometric model specification requires that several challenges be addressed. First, estimated effect sizes from primary studies are heterogeneous due to differences in study-specific characteristics, such as study design, data, and context. We try to model and account for this heterogeneity by including the explanatory variables in the regression model, as described before (Nelson and Kennedy 2009, Stanley and Doucouliagos 2012, Bruns 2017).

Secondly, the precision of the effect-sizes varies between primary studies due to differences in study characteristics. This might violate the homoscedasticity assumption underlying ordinary least squares (OLS) estimation, and hence bias statistical inference based on OLS. The most common way to deal with this problem is to weight the effect sizes by their precision, so that more precise estimates carry more weight in the regression than less precise estimates. In this weighted least squares (WLS) estimation, the estimated standard errors are ideally used as weights. However, many primary studies do not report standard errors. Instead, the number of observations is often used as weights instead (Nelson and Kennedy 2009); we adopted this approach in this study.

However, the implementation of this approach raises another issue. CEs generally have larger numbers of observations in order to reliably estimate the impact of multiple attributes (both biodiversity indicators and non-biodiversity attributes) on WTP than CV studies, which estimate WTP for one or a few particular biodiversity scenarios. This means that the relatively larger number of observations of CEs does not necessarily lead to more precise WTP estimates compared to CV studies. We corrected for this potential imbalance by re-scaling the number of respondents in CEs using the ratio between the average sample size of CEs to CV studies, so that the weight of the average CE estimate is equal to the weight of the average CV estimate. We assessed the impact of this weighting scheme on the results in a robustness analysis (section 4.3).

The third and final challenge is that primary studies often provide multiple estimates that may be correlated with each other. We deal with such potential within-study correlation by calculating clustered standard errors, with clustering at the publication level. In the robustness analysis we assess whether alternative clustering (that is, by underlying dataset instead of by publication) lead to different results.[9]

4. Results and discussion

4.1. Descriptive statistics

The final meta-database includes 159 estimates from 62 publications. The reported mean WTP values vary between US$1 and US$1419, with an arithmetic mean of US$126 for CV studies and US$122 for CEs. The mean WTP values of US$85 and US$79 (converted to US$ 2017) for CV studies and CEs, respectively, are higher than those reported in previous meta-analyses in which both use and non-use values were taken into account (Richardson and Loomis 2009, Hjerpe *et al* 2015). Using the Mann-Whitney test, a significant difference can be detected between the mean WTP values derived from CV and CEs ($\chi^2 = 4.23$, $p = 0.04$), suggesting that the approaches do not generate similar biodiversity non-use welfare estimates. Descriptive statistics for the evidence base (see table 1) suggest that most valuation studies focused on policy responses addressing human threats, while relatively few have focused on other threats or combinations of the two. The latter combination of threats generates substantially higher mean WTP values than valuation studies, in which biodiversity non-use values were elicited under human threats or other threats only. In the case of human threats, mean WTP is substantially higher for agriculture and urban development than for any of the other categories of threats. Furthermore, forests are the highest valued habitats, followed by wetlands, then marine and finally grassland or shrubland habitats. [10] However, using the Mann-Whitney test, no significant differences can be detected between the forest and wetland habitats ($\chi^2 = 0.04$, $p = 0.84$), the forest and marine habitats ($\chi^2 = 0.57$, $p = 0.45$), and the wetland and marine habitats ($\chi^2 = 1.65$, $p = 0.20$). The highest values originate from North America, followed by Oceania. Publications based on data collected in Oceania, South America and Africa are underrepresented. This implies that any policy recommendations

[9]We avoid the use of random-effects models as this requires strict exogeneity; that is, group-level error terms should not be correlated with the explanatory variables. However, this assumption may not be warranted for observations from a wide range of economic valuation studies, and violations of strict exogeneity can lead to biased and inconsistent parameter estimates (Greene 2018, Antonakis *et al* 2019).

[10]Due to the low number of observations, we combined the observations from studies focusing on grassland and shrubland habitats into one category in the meta-regression models.

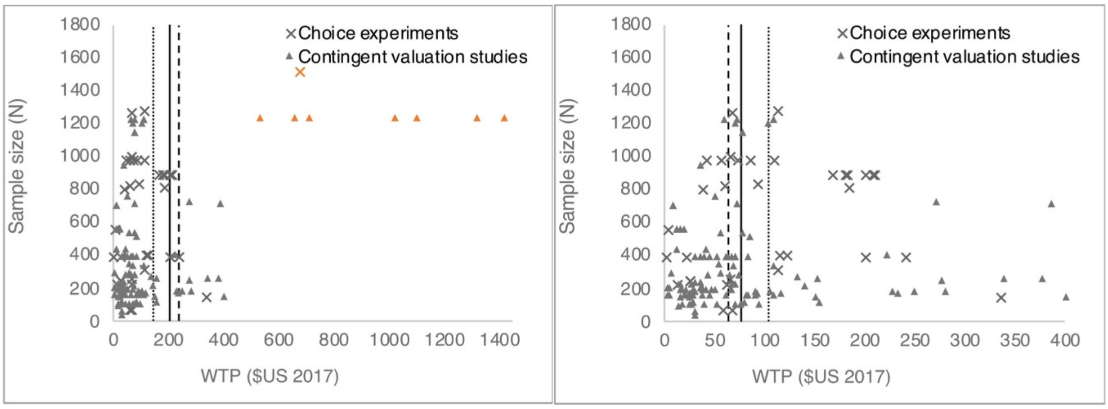

Figure 3. Funnel plots with outliers marked in orange (left panel) and without outliers (right panel). The overall weighted mean is indicated by the solid black line. The weighted means of CV studies and CEs are indicated by the dashed and dotted lines, respectively.

derived from this dataset are biased towards the preferences of North Americans and Europeans.

A closer examination of the estimates in the meta-database revealed that eight estimates from two publications (Mcfadden 1994, Petrolia *et al* 2014) appear to have both a relatively large mean WTP and a large sample size, [11] indicating that these estimates may be highly influential in the meta-analysis. Table 1 shows that the exclusion of these estimates has a considerable impact on the weighted mean WTP value in the database. Hence, we estimate the meta-regression models with and without these outliers to explore the sensitivity of our findings to these outliers.

The evidence collected in the meta-database may be subject to reporting biases. While *p*-hacking describes selective reporting of statistically significant findings at the analysis level within each study (Simmons *et al* 2011, Bruns and Ioannidis 2016), publication bias describes selective reporting of studies that contain statistically significant findings, while studies with non-significant findings may remain in the file drawer (Rosenthal 1979). We use a funnel plot for visual inspection of selective reporting (Egger *et al* 1997, Sterne and Egger 2001). Figure 3 shows the effect-size estimates included in the meta-database plotted against the number of respondents. [12] The left-hand panel shows that the eight estimates from two studies classified as outliers represent comparably large WTP estimates from studies with large sample sizes. The right-hand panel excludes these outliers and the WTP estimates appear more as a funnel, with precise estimates from studies with large sample sizes at the top and less precise estimates at the bottom.

Asymmetry in funnel plots is usually interpreted as an indication of selective reporting. Figure 3 demonstrates a truncation of the funnel at zero. This truncation appears because negative WTP values for environmental goods are generally considered to be implausible because 'the good can simply be ignored if it does not provide utility to the respondent' (Haab and McConnell, 1997, p. 253).[13] Consequently, CV practitioners often remove negative WTP values alongside other protest responses or functional forms are estimated that require strictly positive WTP values (Bohara *et al* 2001). As far as CEs are concerned, alternatives that are considered implausible, such as those that imply negative WTP values, are usually dropped from the range of alternatives presented to CE participants (Bennet and Blamey 2001). Hence, the truncation at zero appears to be due to the research designs used in stated preference studies, which are based on the notion that non-use values cannot be negative. Consequently, the apparent asymmetry of the funnel plot should not be interpreted as an indication of selective reporting. [14] Despite the truncation at zero, the number of WTP estimates around the weighted means are fairly similar, with 54% of both the CM and CV estimates being smaller than the respective weighted means.

Generally, findings from funnel plots need to be interpreted with care, as WTP estimates from various primary studies with heterogeneous characteristics are plotted and some of the observed

[11]We identified the eight potential outliers by adopting a least conservative threshold of 1.96 absolute deviations above the median of the log-transformed WTP values, following the procedure proposed by (Leys *et al.* 2013). The potential outliers (6.28, 6.49, 6.57, 6.93, 7.01, 7.19 and 7.26 for (Mcfadden 1994) and 6.52 (Petrolia *et al* 2014)) are all above the threshold value of 6.26.

[12]We are aware that we do not follow the recommended practice of using standard errors as a measure of precision (Sterne and Egger 2001). However, we could not extract or derive standard errors for almost half of the effect-size estimates, so we rely on the number of primary observations as a proxy measure for precision instead.

[13]Please note that we excluded three negative WTP values from our meta-database. However, these estimates are excluded because the policy scenarios in these studies are likely to lead to reductions in non-market goods other than non-use value (see section 3.2.1).

[14]It is only if one accepts that people can hold negative WTP values based on pure non-use motives that it is possible to argue that the truncation at zero is the result of a selection process. However, to the best of our knowledge, the possibility of negative WTP values that are solely non-use motivated has not been explored to date.

Table 2. Meta-regression models estimated with WLS (N = 159).

Dep.var.: ln(WTP)	Model I (*x = 1 if at least one human threat*)			Model II (*x = 1 if human threats only*)			Signs and significance of common regressors in previous meta-analyses		
	Coeff	Std. Error		Coeff	Std. Error		HHP (2015)	OL (2011)	JH (2009)
Intercept	−0.06	3.56		0.61	3.67		+/0.01	+/0.01	n.s.
Environmental good characteristics									
Biodiversity indicator (baseline = habitat quality)									
Species abundance	0.74	0.65		0.73	0.66				
Species richness	−0.09	0.52		−0.10	0.54				
Habitat type or species affected (baseline = forest habitat)									
Marine habitat	0.44	0.59		0.43	0.59			n.s.	n.s.
Wetland habitat	0.93	0.46	*	1.05	0.47	*			n.s.
Grassland or shrubland habitat	0.30	0.66		0.18	0.67			n.s.	n.s.
Bird species	−0.70	0.70		−0.96	0.71				
Mammal species	−1.16	0.83		−1.02	0.83				
Other species	−0.19	0.51		−0.31	0.51				
Recovery or improvement of biodiversity (baseline = avoid biodiversity loss)	−0.46	0.35		−0.55	0.35		+/0.01	n.s.	n.s.
Outcome uncertainty	−1.30	0.49	**	−1.25	0.51	*			
Human threats (x)	1.14	0.41	**	0.61	0.39				
Methodological characteristics									
Face-to-face interview	−0.10	0.36		−0.001	0.37			+/0.10	n.s.
Payment schedule	−0.62	0.35	.	−0.76	0.37	*	–/0.05	–/0.10	n.s.
Voluntary payments	−0.54	0.31	.	−0.49	0.31		–/0.001		n.s.
Household response	0.29	0.31		0.40	0.30			n.s.	n.s.
Protest responses removed	0.70	0.29	*	0.75	0.30	*			
CE (baseline is CV)	−0.11	0.59		0.16	0.62		+/0.1		
CE: Mixed logit	−0.22	0.57		−0.36	0.59				
CV: Open-Ended	−0.60	0.44		−0.55	0.47			–/0.10	–/0.01
CV: Payment card	−0.87	0.53		−0.63	0.53				
CV: Non-parametric	−0.16	0.18		−0.17	0.18				
Sample characteristics									
Study year (1979 = 0)	−0.03	0.03		−0.03	0.03		–/0.01	–/0.01	n.s.
CV: Non-use motivation only	−1.23	0.42	**	−1.40	0.37	***			
Non-users only	−0.42	0.56		−0.52	0.56				
Context variables									
North-America	0.49	0.48		0.61	0.50		n.s.	–/0.001	
ln(GDP per capita)	0.44	0.39		0.41	0.40		+/0.001	+/0.01	n.s.
adjusted R^2	0.54			0.52					
F-test	8.36			7.53					
N	159			159			127	317	111

Notes: Standard errors clustered by primary publications are reported. Significance levels indicated by . ($p < 0.10$), * ($p < 0.05$), ** ($p < 0.01$), and *** ($p < 0.001$). The three rightmost columns indicate the signs and significance of the full models estimated by Hjerpe *et al* 2015 (HHP), Ojea and Loureiro 2011 (OL), and Jacobsen and Hanley 2009 (JH), respectively.

patterns may be explained by between-study heterogeneity rather than selective reporting. We also test for selective reporting by comparing peer-reviewed publications with grey literature. In the absence of selective reporting, peer-reviewed publications should produce estimates that are similar to estimates from the grey literature. We estimate a third model in which we included a dummy variable that is set to unity for estimates from peer-reviewed publications in the multivariate analysis (Model III in table 3).

4.2. Regression results and discussion

The principal objectives of this meta-analysis are to estimate an updated non-use valuation function that can be included in climate change damage assessments, synthesizing four decades of biodiversity valuation research, and to test the hypothesis

Table 3. Meta-regression models estimated with WLS and potential outliers excluded (N = 151).

Dep.var.: ln(WTP)	Model I (*x = 1 if at least one human threat*)			Model II (*x = 1 if only human threats*)			Model III with control for selective reporting (*x = 1 if at least one human threat*)		
	Coeff	Std. Error		Coeff	Std. Error		Coeff	Std. Error	
Intercept	1.17	3.02		1.07	3.11		0.25	3.31	
Environmental good characteristics									
Biodiversity indicator (baseline = habitat quality)									
Species abundance	1.03	0.62		1.01	0.63		1.03	0.63	
Species richness	0.25	0.50		0.28	0.52		0.27	0.51	
Habitat type or species affected (baseline = forest habitat)									
Marine habitat	0.61	0.53		0.61	0.53		0.65	0.54	
Wetland habitat	1.10	0.44	*	1.12	0.44	*	0.96	0.44	*
Grassland or shrubland habitat	0.29	0.68		0.23	0.68		0.23	0.69	
Bird species	−0.49	0.66		−0.58	0.66		−0.44	0.67	
Mammal species	−1.40	0.84	.	−1.34	0.83		−1.36	0.87	
Other species	0.36	0.46		0.30	0.45		0.29	0.47	
Recovery or improvement of biodiversity (baseline = avoid biodiversity loss)	−0.37	0.34		−0.41	0.35		−0.40	0.35	
Outcome uncertainty	−1.06	0.49	*	−1.02	0.49	*	−1.08	0.50	*
Human threats (x)	0.89	0.39	*	0.73	0.38	.	1.05	0.39	**
Methodological characteristics									
Face-to-face interview	−0.10	0.35		−0.06	0.36		−0.09	0.36	
Payment schedule	−1.09	0.35	**	−1.11	0.35	**	−1.02	0.36	**
Voluntary payments	−0.30	0.31		−0.26	0.33		−0.28	0.31	
Household response	0.52	0.31	.	0.57	0.31	.	0.43	0.31	
Protest responses removed	0.35	0.24		0.38	0.25		0.33	0.24	
CE (baseline is CV)	−0.44	0.50		−0.44	0.50		−0.47	0.51	
CE: Mixed logit	0.39	0.52		0.39	0.53		0.37	0.53	
CV: Open-Ended	0.11	0.25		0.11	0.25		0.09	0.25	
CV: Payment card	−0.64	0.53		−0.54	0.54		−0.53	0.58	
CV: Non-parametric	−0.26	0.16		−0.28	0.17		−0.30	0.17	.
Sample characteristics									
Study year (1979 = 0)	−0.01	0.02		−0.01	0.02		−0.01	0.02	
CV: Non-use motivation only	−0.68	0.44		−0.76	0.44	.	−0.48	0.44	
Non-users only	−0.47	0.53		−0.53	0.54		−0.27	0.58	
Context variables									
North-America	0.09	0.48		0.11	0.49		0.08	0.49	
ln(GDP per capita)	0.26	0.32		0.28	0.33		0.30	0.33	
Peer-reviewed publication							0.49	0.67	
adjusted R^2	0.47			0.46			0.47		
F-test	6.18			6.00			6.00		

Note: Significance levels indicated by. ($p < 0.10$), * ($p < 0.05$), ** ($p < 0.01$), and *** ($p < 0.001$).

that non-use values for policy responses that either improve biodiversity or avoid biodiversity loss vary depending on the policy description; that is, whether the valuation takes place in the context of human threats or other threats. Overall, the adjusted R^2 values of the models with and without outliers (see table 2 and 3), which vary between 0.46 and 0.54, are similar to or higher than the adjusted R^2 value of many meta-regression models in the field of environmental and resource economics (median adjusted $R^2 = 0.44$) (Nelson and Kennedy 2009). Based on the meta-regression models with outliers, we find a statistically significant effect of the 'human threats' variable (denoted as x) on the estimated WTP values at the $p < 0.01$ level for Model I (in which the 'human threats' variable is 1 if policy addresses at least one human threat), but not for Model II (in which the 'human threats' variable is 1 if policy addresses only human threats). For the meta-regression models without outliers, we reject the null hypothesis at the $p < 0.05$ and $p < 0.10$ level for Models I and II, respectively. This means that the meta-regression models suggest some support for the hypothesis that the natural logarithm of WTP (hereafter, WTP) for policy

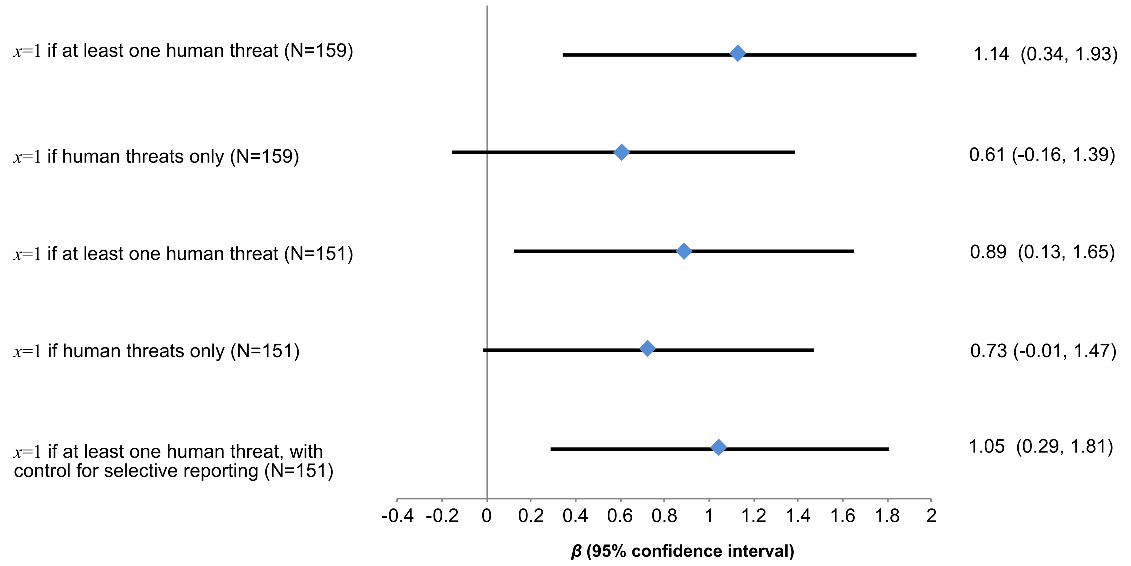

Figure 4. Magnitudes and confidence intervals of the 'human threats' coefficient in the different model specifications (the 'human threats' variable is denoted as x).

responses that address the negative impact of human activities on biodiversity are significantly higher than the WTP for policy responses in the face of other threats. Furthermore, using F-tests to compare Models I and II in table 2 with their restricted versions in which the coefficient of the 'human threats' variable is set to zero, we find that this variable contributes significantly to the explanatory power of Model I only (for Model I: $\chi^2 = 7.50$ ($p = 0.007$); for Model II: $\chi^2 = 2.61$ ($p = 0.107$), respectively). For the models without outliers (table 3), the 'human threats' variable contributes significantly to the explanatory power at the 5% significance level or better for all models (for Model I: $\chi^2 = 5.05$ ($p = 0.008$); for Model II: $\chi^2 = 5.91$ ($p = 0.02$); for Model III: $\chi^2 = 5.77$ ($p = 0.004$)). The magnitudes and 95% confidence intervals of the 'human threats' variable in the different model specifications are visualized in figure 4.

Turning to the other environmental good characteristics, non-use values are not sensitive to the biodiversity indicator used in all of the models in tables 2 and 3. Furthermore, the habitat types or the taxonomic group to which a species belongs do not significantly affect WTP values, apart from wetland habitats, which attract significantly higher non-use values in all models. These findings call into question whether lay people, as respondents in stated preferences surveys, are able to distinguish between conservation of different biodiversity types, which is a concern also raised by (Hanley *et al.* 1995). Previous meta-analyses of use and non-use values of biodiversity conservation also found that habitat types were generally insignificant predictors of WTP (see three rightmost columns in table 2). Furthermore, no significant effect can be detected for the type of welfare measure that is used in the valuation studies; that is, whether the policy involves avoiding a biodiversity loss or improvement. (Hjerpe *et al.* 2015) found that improvements yield significantly higher WTP values than avoided losses. In line with our expectations (e.g. Brouwer and Neverre 2018), we find that outcome uncertainty have a significant impact on mean stated WTP in all models.

With regard to the methodological characteristics, using face-to-face interviews (baseline: mail or phone survey) does not significantly affect WTP in any of the models. This contrasts with the results of the meta-analysis by (Ojea and Loureiro 2011), who found a significant positive effect of in-person interviews and interpreted this as evidence of social responsibility bias. However, the other meta-analyses do not find a significant effect of welfare measure. As in previous meta-analyses, whether payments are recurring (versus a one-off payment) has a significant negative impact on WTP in all models. Payment vehicles—particularly whether payments are voluntary or mandatory—do not significantly influence stated WTP values, except in Model I with outliers (table 2). WTP estimates from studies in which respondents represent their household are significantly higher in all models without outliers (table 3). Previous meta-analyses did not find this effect. As expected, the removal of protest responses leads to significantly higher WTP values, but this effect is significant in the models with outliers only (table 2). An important finding is that CEs do not provide significantly different WTP estimates compared to CV studies in any of the models, despite the fact that we assumed a maximum change in the biodiversity-related indicators in the calculation of mean WTP values derived from CEs. Furthermore, the variables indicating whether CV estimates are parametric or non-parametric, and whether CE estimates are derived from a mixed or conditional logistic regression, do not have any significant impact on WTP values, except in Model III (table 3) where non-parametric estimates are significantly lower. Contrary to expectations (e.g. Bateman and Garrod 1995), CV-based WTP estimates obtained from an open-ended WTP elicitation format are not significantly different from dichotomous choice estimates, while payment-card WTP values are not significantly different from dichotomous choice estimates in any of the models.

As far as the sample characteristics are concerned, study year does not have a significant impact in any of the models. This finding contrasts with those of previous meta-analyses, which found a negative impact on WTP. Furthermore, we find that the 'apportioning' method leads to a significantly lower WTP in Models I and II with outliers (table 2) and Model II without outliers (table 3), compared to the reference category, that is, studies that assumed that WTP values comprise mostly or exclusively non-use values. The 'non-user' method does not lead to different WTP results compared to the reference category. This finding contrasts with a meta-analysis of non-use values of surface water quality, which found that the 'non-user' method had a negative impact on non-use values (Johnston *et al* 2018). More generally, this finding contradicts the argument that the non-use values of non-users are different from those held by users. An alternative explanation is that the estimates in the baseline category are essentially based on non-user samples due to the remoteness or minimal use value of the environmental good.

With regard to the context characteristics, we did not find a significant impact of ln(GDP per capita) on mean WTP values. Previous meta-analyses found a positive impact of GDP per capita on WTP values. Also, the variable reflecting that studies were conducted in North America does not affect WTP estimates, whereas (Ojea and Loureiro 2011) found that this variable has a negative impact on WTP.

Finally, as far as selective reporting is concerned, we do not reject the null hypothesis that the estimates from peer-reviewed publications are equal to the effect sizes reported by the grey literature. However, the sample contains only seven estimates from the grey literature implying that this finding should not be over-interpreted.

We used the meta-regression models in table 2 and 3 to predict mean annual WTP by means of within-sample prediction. We set the 'human threats' variable to one to calculate mean WTP for biodiversity losses caused by humans and zero for those that are not. To obtain annual values per capita, we set the 'payment schedule' variable to 1 (that is, to annual payments) and the 'household' variable to zero (that is, to individual WTP values). All other variables are set to their original values as in the primary studies. We calculated the arithmetic mean over all WTP estimates divided by GDP per capita in 2017 in the country in which each primary study was conducted. We found that the mean annual WTP ranges between 0.2% and 0.4% of GDP per capita for avoiding human-caused biodiversity losses and 0.1% and 0.2% for avoiding biodiversity losses not caused by humans (see table 4).

Although we did not find a significant effect of GDP per capita on WTP values in our meta-regression analysis, the coefficient estimates (0.26–0.44) reflecting constant income elasticities of public WTP are close to the values reported, for example, in Jacobsen and Hanley's (2009) global meta-analysis. We also found that, by estimating reduced form models that better fit transferability conditions and only include a few variables for which secondary data are available, the income elasticity remains more or less the same (0.17–0.33) and increases in statistical significance, but the stability of the income elasticities in these models is low. Whereas some arguments have been put forward that support income elasticities of WTP for environmental goods that are higher than one (Krutilla and Fisher 1975), this is not commonly observed in the stated preference literature (e.g. Kriström and Riera 1996, Barbier *et al* 2017), indicating that WTP grows at a slower rate than GDP. Since global GDP per capita is expected to grow by 2.4% per year until 2100 (Leimbach *et al* 2017), we expect that the fraction of GDP that the public is willing to pay for biodiversity conservation will decrease over time.

4.3. Robustness checks

We conducted a variety of checks to test the robustness of our regression results. First, we estimated the models using OLS estimation (see table B1 in appendix B). The statistical significance of several variables differs. The 'protest responses removed' variable is insignificant in Model I and the voluntary payment variable is significant in Model II when using OLS estimation. Regarding the primary hypothesis of this paper, we find that the 'human threats' variable has a statistically significant effect at the 5% confidence level or better for Models I and II. Second, we calculated robust standard errors based on clustering by primary dataset instead of by publication. We found that the statistical significance remains identical for all variables (see table OA1 in the online appendix (available at stacks.iop.org/ERL/15/073003/mmedia)). Third, we explored the robustness of the results to the chosen weighting scheme by estimating the WLS models with observations weighted by the number of respondents (table OA2 in the online appendix), and by estimating the WLS models separately for CV studies (table OA3 in the online appendix). The significance of all of the

Table 4. Mean annual WTP for biodiversity conservation as a percentage of GDP per capita in 2017 (95% confidence intervals between brackets).

	Outliers included		Outliers excluded		
Biodiversity loss is human-caused	Model I (*x* = *1 if at least one human threat)*	Model II (*x* = *1 if human threats only)*	Model I (*x* = *1 if at least one human threat)*	Model II *(x* = *1 if only human threats)*	Model III with control for selective reporting *(x* = *1 if at least one human threat)*
Yes	0.34 [0.29, 0.40]	0.31 [0.25, 0.36]	0.35 [0.29, 0.40]	0.18 [0.15, 0.21]	0.40 [0.33, 0.47]
No	0.11 [0.09, 0.13]	0.17 [0.14, 0.19]	0.11 [0.09, 0.13]	0.09 [0.07, 0.10]	0.10 [0.08, 0.12]

Note: The standard errors of the sample means are used to calculate the 95% confidence intervals.

variables does not change in these models, except that the 'voluntary payment' variable is insignificant in the model with observations weighted by the number of respondents. We did not run the models on CEs only, due to the small number of CE observations (N = 35). We also explored robustness with respect to the common meta-regression model in economics (Stanley and Doucouliagos 2012) that controls for a potential association between estimated effect sizes and their precisions (see table OA4 in the online appendix). Again, we find a statistically significant effect of the 'human threats' variable for Models I and II at the 5% confidence level. Based on these robustness checks, we conclude that the threat addressed by the valued biodiversity conservation policy may be a relevant predictor of non-use values, but also that the regression results depend on the applied classification rule, the inclusion or exclusion of outliers, and the weighting scheme.

5. Conclusions and discussion

With the adoption of the Paris Agreement and the SDGs, governments agreed to invest heavily in combatting climate change. The present study synthesized four decades of empirical evidence of what may be an important benefit of fulfilling these commitments: the non-use value of biodiversity conservation. The overall lack of empirical studies that estimate public WTP for biodiversity conservation in the face of anthropogenic climate change suggests that these benefits have, to date, not played a very prominent role in the evaluation of climate change policy. In the absence of specific estimates in the context of anthropogenic climate change, we (1) synthesized non-use values for biodiversity conservation in the context of various anthropocentric and non-anthropocentric threats and (2) examined the appropriateness of integrating such biodiversity non-use values into climate change damage functions.

Based on 159 non-use value estimates from 62 primary studies, we found an arithmetic mean public willingness to pay for policies that aim to preserve biodiversity of US$118 per household per year or US$149 per household when they are asked to make a one-off payment. Compared with mean WTP values reported in previous meta-analyses that included both use and non-use values, we conclude that non-use values constitute an important part of the total economic value of biodiversity. Furthermore, we find that non-use values are not sensitive to the type of biodiversity indicator, the particular habitats, or the taxonomic groups being valued in the primary stated preference studies. Furthermore, we do not find a statistically significant difference between non-use values from contingent valuation studies and choice experiments. Regarding the relevance of the nature of the threat to biodiversity, we find some evidence that biodiversity non-use values may depend on whether a proposed policy addresses negative impacts from human threats. We find that the effect of human threats being mentioned in the policy description on the estimated WTP is statistically significant in all models except when outliers are included and a strict classification for the 'human threats' variable is applied. This implies that, when assessing the biodiversity component of climate change damages, it is important to recognize that valuations of non-human causes may underestimate the value losses caused by human-caused climate change. Extrapolating further, we argue that public support for mitigating the impacts of climate change on biodiversity is contingent on public understanding that these impacts are in fact anthropogenic, which is an important communication challenge (Moser 2010, Van Prooijen and Sparks 2014).

Based on the meta-regression analysis, we predict that the annual non-use value of biodiversity in the face of human threats ranges from 0.2% to 0.4% of global GDP per capita in 2017, and 0.1–0.2% in the face of other threats. This implies that biodiversity non-use values may constitute a relevant economic benefit of climate action that should not be overlooked in cost-benefit analyses. Furthermore, the DICE and FUND models, which are commonly used to inform climate change policy, may underestimate actual climate change damages by assuming an annual WTP of 0.1% of GDP per capita for ecosystem and species conservation. Our findings suggest that such an assumption does not reflect the premium that the public is willing to pay to avoid biodiversity losses caused by humans.

This meta-analysis has several limitations. Firstly, it only includes primary valuation studies in which respondents are informed about policies that address a variety of biodiversity threats, but not specifically about human-caused climate change as a threat to biodiversity. Respondents may report different non-use values for biodiversity conservation if it is aimed at combatting anthropogenic climate change impacts. This may, among other things, depend on prior beliefs about anthropogenic climate change, which is an important knowledge gap that needs to be addressed in future research. Second, our estimates of mean annual WTP are based on scenarios in which policy interventions prevent a fixed amount of biodiversity loss. Hence, these non-use values need to be adjusted for the extent of biodiversity loss due to global temperature increases before they can be integrated into global climate change damage functions. This is an important avenue for future research that is beyond the scope of the present study. Third, our results may be biased towards the preferences of North Americans and Europeans due to a lack of studies in other regions of the world. The fourth limitation is that the number of estimates from studies focusing on non-human threats is relatively small. Hence, our results should be interpreted with caution as the number of non-use value estimates for biodiversity losses due to other threats is relatively small (approximately 10% of the observations). Finally, due to the relatively imprecise definition of biodiversity in the majority of economic valuation studies, which itself is an important criticism on the biodiversity valuation literature (Nunes and Van den Bergh 2001), survey participants may have interpreted the same biodiversity change in different ways. This could be problematic given that WTP values may depend on the biodiversity indicator and the magnitude of the change on the indicator, such as the quantitative change of the number of individuals within a species or the quantitative change of the number of species. Future research should consider whether providing more detailed information about biodiversity changes affects WTP values.

Acknowledgments

AN and SL are funded by fellowships of the Research Foundation Flanders (11G2319N and 12G5418N, respectively).

Conflict of interest statement

We certify that there are no financial or non-financial conflicts of interest to disclose.

Data availability statement

The data that support the findings of this study are openly available in the IOP Publishing Figshare repository.

Appendix A

Table A1. List of primary studies included in the meta-database.

1. Aanesen *et al* 2015[a]
2. Amirnejad *et al* 2006
3. Armstrong *et al* 2017[a]
4. Bateman 1996
5. Bennett 1984
6. Berrens *et al* 1996
7. Börger and Hattam 2017[a]
8. Börger *et al* 2014[a]
9. Borzykowski *et al* 2018
10. Broberg 2007
11. Brouwer *et al* 2016
12. Brown *et al* 1996
13. Carneiro and Carvalho 2014
14. Carson and Mitchell 2003
15. Carson *et al* 1995
16. Champ *et al* 1997
17. Chang *et al* 2011
18. Drake and Jones 2017
19. Ekstrand and Loomis 1998
20. Farber and Griner 2000[a]
21. Gilbert *et al* 1991
22. Hageman 1985
23. Hanley *et al* 2003
24. Horton *et al* 2003
25. Hoyos *et al* 2012[a]
26. Jacobsen *et al* 2012[a]
27. Jobstvogt *et al* 2014[a]
28. Kontogianni *et al* 2012
29. Kreye *et al* 2016[a]
30. Logar *et al* 2019[a]
31. Loomis *et al* 1994
32. Martínez-Espiñeira 2007
33. Mcfadden 1994
34. Mcvittie and Moran 2010[a]
35. Morrison *et al* 1999[a]
36. Morse-Jones *et al* 2012[a]
37. Norton and Hynes 2014[a]
38. O'Garra 2009
39. Oglethorpe and Miliadou 2000
40. Petrolia *et al* 2014[a]
41. Reaves *et al* 1999
42. Rollins and Lyke 1998
43. Rudd *et al* 2016[a]
44. Sanders *et al* 1990
45. Schaafsma *et al* 2013
46. Schaafsma *et al* 2012[a]
47. Shechter *et al* 1998
48. Stanley 2005
49. Subade and Francisco 2014
50. Sutherland and Walsh 1985
51. Tisdell *et al* 2005
52. Veisten *et al* 2004
53. Veisten and Navrud 2006
54. Wallmo and Kosaka 2017[a]
55. Walsh *et al* 1990
56. Walsh *et al* 1984
57. White *et al* 1997
58. Whitehead *et al* 1995
59. Willis *et al* 1995
60. Willis and Garrod 1998
61. Windle and Rolfe 2005[a]

[a]Choice experiment

Appendix B

Table B1. Meta-regression estimated with OLS (N = 159).

Dep.var.: ln(WTP)	Model I (*x = 1 if at least one human threat*) Coeff	Std. Error		Model II (*x = 1 if only human threats*) Coeff	Std. Error	
Intercept	−0.04	3.56		0.34	3.67	
Environmental good characteristics						
Biodiversity indicator (baseline = habitat quality)						
Species abundance	0.36	0.65		0.32	0.66	
Species richness	0.24	0.52		0.27	0.54	
Habitat type or species affected (baseline = forest habitat)						
Marine habitat	0.66	0.59		0.67	0.59	
Wetland habitat	0.82	0.46	.	0.93	0.47	*
Grassland or shrubland habitat	−0.25	0.66		−0.33	0.67	
Bird species	−0.40	0.70		−0.54	0.71	
Mammal species	−1.06	0.83		−0.93	0.83	
Other species	−0.11	0.51		−0.11	0.50	
Recovery or improvement of biodiversity (baseline = avoid biodiversity loss)	−0.43	0.35		−0.48	0.35	
Outcome uncertainty	−0.89	0.49	.	−0.89	0.51	.
Human threats (x)	1.06	0.41	**	0.65	0.39	.
Methodological characteristics						
Face-to-face interview	−0.30	0.36		−0.22	0.37	
Payment schedule	−0.66	0.35	.	−0.77	0.37	*
Voluntary payments	−0.69	0.31	*	−0.63	0.31	*
Household response	0.32	0.31		0.43	0.30	
Protest responses removed	0.46	0.29		0.52	0.30	.
CE (baseline is CV)	−0.34	0.59		−0.19	0.62	
CE: Mixed logit	−0.17	0.57		−0.24	0.59	
CV: Open-Ended	−0.02	0.44		0.05	0.47	
CV: Payment card	−0.57	0.53		−0.44	0.53	
CV: Non-parametric	−0.12	0.18		−0.13	0.18	
Sample characteristics						
Study year (1979 = 0)	−0.03	0.03		−0.02	0.03	
CV: Non-use motivation only	− 0.93	0.42	*	−1.13	0.37	**
Non-users only	−0.52	0.56		−0.66	0.56	
Context variables						
North-America	0.36	0.48		0.44	0.50	
ln(GDP per capita)	0.42	0.39		0.41	0.40	
adjusted R^2	0.43			0.42		
F-test	5.67			5.29		

Notes: Standard errors clustered by primary publications are reported. Significance levels indicated by . ($p < 0.10$), * ($p < 0.05$), ** ($p < 0.01$), and *** ($p < 0.001$).

ORCID iDs

Anne Nobel https://orcid.org/0000-0003-2460-8566
Sebastien Lizin https://orcid.org/0000-0002-3320-6406
Roy Brouwer https://orcid.org/0000-0002-0525-2050
Stephan B Bruns https://orcid.org/0000-0002-3028-9699
David I Stern https://orcid.org/0000-0001-6595-4268
Robert Malina https://orcid.org/0000-0002-1886-286X

References

Aanesen M, Armstrong C, Czajkowski M, Falk-Petersen J, Hanley N and Navrud S 2015 Willingness to pay for unfamiliar public goods: preserving cold-water coral in Norway *Ecol. Econ.* **112** 53–67

Ajzen I 2005 *Attitudes, Personality and Behavior* (Berkshire, UK: McGraw-Hill Education)

Allen C D, Macalady A K, Chenchouni H, Bachelet D, Mcdowell N, Vennetier M and Cobb N 2010 A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests *For. Ecol. Manage.* **259** 660–84

Amirnejad H, Khalilian S, Assareh M H and Ahmadian M 2006 Estimating the existence value of north forests of Iran by using a contingent valuation method *Ecol. Econ.* **58** 665–75

Anthoff D and Tol R S J 2013 FUND v3.7 scientific documentation 1–26 Retrieved 12 May 2019 (http://www.fund-model.org.)

Antonakis J, Bastardoz N and Rönkkö M 2019 The endogeneity problem in random intercept models: are most published results likely false? *Acad. Manage. Proc.* **2019** 1

Armstrong C W, Vondolia G K, Aanesen M, Kahui V and Czajkowski M 2017 Use and non-use values in an applied bioeconomic model of fisheries and habitat connections *Mar. Resour. Econ.* **32** 351–69

Arrow K, Solow R, Portney P R, Leamer E E, Radner R and Schuman H 1993 Report of the NOAA panel on contingent valuation *Fed. Regist.* **58** 4601–14

World Bank 2019 World bank open data Retrieved 12 May 2019 (https://data.worldbank.org/)

Barbier E B, Czajkowski M and Hanley N 2017 Is the income elasticity of the willingness to pay for pollution control constant? *Environ. Resour. Econ.* **68** 663–82

Bateman I J and Garrod G D 1995 Elicitation and truncation effects in contingent valuation studies *Ecol. Econ.* **12** 161–79

Bateman I J and Langford I H 1996 Non-users' willingness to pay for a national park: an application and critique of the contingent valuation method *Reg. Stud.* **31** 571–82

Bateman I J and Jones A P 2003 Contrasting conventional with multi-level modeling approaches to meta-analysis: expectation consistency in UK woodland recreation values *Land Econ.* **79** 235–58

Bennett J W 1984 Using direct questioning to value the existence benefits of preserved natural areas *Aust. J. Agric. Econ.* **28** 136–52

Bergstrom J C and Taylor L O 2006 Using meta-analysis for benefits transfer: theory and practice *Ecol. Econ.* **60** 351–60

Bennet J W and Blamey R 2001 *The Choice Modeling Approach to Environmental Valuation* (Massachusetts: Edward Elgar)

Berrens R P, Ganderton P and Silva C L 1996 Valuing the protection of minimum instream flows in New Mexico *J. Agric. Resour. Econ.* **21** 294–307

Bohara A K, Kerkvliet J and Berrens R P 2001 Addressing negative willingness to pay in dichotomous choice contingent valuation *Environ. Resour. Econ.* **20** 173–95

Bonen A, Semmler W and Klasen S 2014 Economic damages from climate change: a review of modeling approaches. *Working Paper Series Infrastructure Against Climate Change* (New York: Schwartz Center for Economic Policy Analysis) pp 1–65

Börger T and Hattam C 2017 Motivations matter: behavioural determinants of preferences for remote and unfamiliar environmental goods *Ecol. Econ.* **131** 64–74

Börger T, Hattam C, Burdon D, Atkins J P and Austen M C 2014 Valuing conservation bene fi ts of an offshore marine protected area *Ecol. Econ.* **108** 229–41

Borzykowski N, Baranzini A and Maradan D 2018 scope effects in contingent valuation: does the assumed statistical distribution of WTP matter? *Ecol. Econ.* **144** 319–29

Boyle K, Morrison M and Taylor L 2004 Why value estimates generated using choice modelling exceed contingent valuation: further experimental evidence Conf. Paper presented at the Australian Agricultural and Resource Economics Society Conf.

Broberg T 2007 *Assessing the Non-timber Value of Old-growth Forests in Sweden Department of Economics* (Umeå. Sweden: Working paper SE-901 87. Department of Economics, Umeå University)

Brooks W R and Newbold S C 2014 An updated biodiversity nonuse value function for use in climate change integrated assessment models *Ecol. Econ.* **105** 342–9

Brouwer R, Logar I and Sheremet O 2017 Choice consistency and preference stability in test-retests of discrete choice experiment and open-ended willingness to pay elicitation formats *Environ. Resour. Econ.* **68** 729–51

Brouwer R, Brouwer S, Eleveld M A, Verbraak M and Wagtendonk A J 2016 Public willingness to pay for alternative management regimes of remote marine protected areas in the North Sea *Mar. Policy* **68** 195–204

Brouwer R and Neverre N 2018 A global meta-analysis of groundwater quality valuation studies *Eur. Rev. Agric. Econ.* 1–40

Brown T C, Champ P A, Bishop R C and Mccollum D W 1996 Which response format reveals the truth about donations to a public good? *Land Econ.* **72** 152–66

Bruns S B and Ioannidis J P 2016 P-curve and p-hacking in observational research *PLoS One* **11** 2

Bruns S B 2017 Meta-regression models and observational research *Oxford Bull. Econ. Stat.* **79** 0305–9049

Bulte E, Gerking S, List J A and De Zeeuw A 2005 The effect of varying the causes of environmental problems on stated WTP values: evidence from a field study *J. Environ. Econ. Manage.* **49** 330–42

Carneiro D Q and Carvalho A R 2014 Ocean & coastal management payment vehicle as an instrument to elicit economic demand for conservation *Ocean Coastal Manage.* **93** 1–6

Carson R, Haneman W M, Kopp R J, Krosnick J A, Mitchel R C, Presser S and Smith V K 1995 Temporal reliability of estimates from contingent valuation *Land Econ.* **73** 151–63

Carson R T and Mitchell R C 2003 Contingent valuation and lost passive use: damages from the exxon valdez oil spill *Environ. Resour. Econ.* **25** 257–86

Champ P A, Bishop R C, Brown T C and Mccollum D W 1997 Using donation mechanisms to value nonuse benefits from public goods *J. Environ. Econ. Manage.* **33** 151–62

Champ P A, Flores N E, Brown T C and Chivers J 2002 Contingent Valuation and Incentives *Land Econ.* **78** 591–604

Chang W, Lantz V A and Maclean D A 2011 Social benefits of controlling forest insect outbreaks: a contingent valuation analysis in two canadian provinces *Can. J. Agric. Econ.* **59** 383–404

Czajkowski M, Hanley N and Lariviere J 2016 Controlling for the effects of information in a public goods discrete choice model *Environ. Resour. Econ.* **63** 523–44

Czech B, Krausman P R and Borkhataria R 1998 Social construction, political power, and the allocation of benefits to endangered species *Conserv. Biol.* **12** 1103–12

Delong D C 1996 Defining biodiversity *Wildl. Soc. Bull.* **24** 738–49

Díaz S, Demissew S, Carabias J, Joly C, Lonsdale M, Ash N and Zlatanova D 2015 The IPBES conceptual framework - connecting nature and people *Curr. Opin. Environ. Sustainability* **14** 1–16

Drake B and Jones G 2017 Public value at risk from phytophthora ramorum and phytophthora kernoviae spread in England and Wales *J. Environ. Manage.* **191** 136–44

Egger M, Smith G D, Schneider M and Minder C 1997 Bias in meta-analysis detected by a simple, graphical test *Bus. Manage. J.* **315** 629–34

Ekstrand E R and Loomis J 1998 Incorporating respondent uncertainty when estimating willingness to pay for protecting critical habitat for threatened and endangered fish *Water Resour. Res.* **34** 3149–55

Farber S and Griner B 2000 Valuing watershed quality improvements using conjoint analysis *Ecol. Econ.* **34** 63–76

Gilbert A, Glass R and More T 1991 The economic value of wilderness *Valuation of Eastern Wilderness: Extramarket Measures of Public Support* (Jackson, WY: Forest Service, US Department of Agriculture) pp 57–70

Greene D W 2018 *Econometric Analysis* 7th Edition edn (New York: Pearson)

Haab T C and Mcconnel K E 1997 Referendum models and negative willingness to pay: alternative solutions *J. Environ. Econ. Manage.* **32** 251–70

Haddaway N, Macura B, Whaley P and Pullin A 2017 ROSES flow diagram for systematic reviews. Reporting Standards for Systematic Evidence Syntheses (https://doi.org/10.6084/m9.figshare.5897389)

Hageman R 1985 Valuing Marine Mammal Populations: Benefit Valuations in a Multi-species Ecosystem *Technical Report LJ-85-22* (San Diego: San Diego State University)

Hamilton A J 2005 Species diversity or biodiversity? *J. Environ. Manage.* **75** 89–92

Hanley N D, Schläpfer F and Spurgeon J 2003 Aggregating the benefits of environmental improvements: distance-decay functions for use and non-use values *J. Environ. Manage.* **68** 297–304

Hanley N, Spash C and Walker L 1995 Problems in valuing the benefits of biodiversity protection *Environ. Resour. Econ.* **5** 249–72

Hensher D A, Rose J M and Greene W H 2005 *Applied Choice Analysis* (Cambridge: Cambridge University Press)

Hjerpe E, Hussain A and Phillips S 2015 Valuing type and scope of ecosystem conservation: A meta-analysis *J. Forest Econ.* **21** 32–50

Homer P M and Kahle L R 1988 A structural equation test of the value-attitude-behavior hierarchy *J. Pers. Soc. Psychol.* **54** 638–46

Hope C 2012 The social cost of CO2 from the PAGE09 model *Economics Discussion Papers No. 2011–39* (www.economics-ejournal.org/economics/discussionpapers/2011-39)

Horton B, Colarullo G, Bateman I J and Peres C A 2003 Evaluating non-user willingness to pay for a large-scale conservation programme in Amazonia: A UK/Italian contingent valuation study *Environ. Conserv.* **30** 139–46

Howard P H and Sterner T 2014 Loaded DICE: refining the meta-analysis approach to calibrating climate damage functions 2014 Annual Meeting July 27–29 2014 (Minneapolis: Agricultural and Applied Economics Association)

Hoyos D, Mariel P, Pascual U and Etxano I 2012 Valuing a natura 2000 network site to inform land use options using a discrete choice experiment: an illustration from the Basque Country *J. Forest Econ.* **18** 329–44

IPCC 2014 *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva: Switzerland)

IPCC 2018 Summary for policymakers *Global Warming of 1.5°C. An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty* ed V P Masson-Delmotte *et al* (Geneva, Switzerland: World Meteorological Organization) p 32

IPCC 2019 Summary for Policymakers *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems* P R Shukla, *et al* in press pp 3–36

IUCN 2019 Habitats classification scheme (version 3.1) Retrieved on January 15 2019 (https://www.iucnredlist.org/resources/habitat-classification-scheme)

Jacobsen J B and Hanley N 2009 Are there income effects on global willingness to pay for biodiversity conservation? *Environ. Resour. Econ.* **43** 137–60

Jacobsen J B, Lundhede T H and Thorsen B J 2012 Valuation of wildlife populations above survival *Biodivers. Conserv.* 543–63

Jobstvogt N, Hanley N, Hynes S, Kenter J and Witte U 2014 Twenty thousand sterling under the sea: estimating the value of protecting deep-sea biodiversity *Ecol. Econ.* **97** 10–19

Johnston R J, Besedin E Y and Holland B M 2018 Modeling distance decay within valuation meta-analysis *Environ. Resour. Econ.* **72** 657–90

Johnston R J, Besedin E Y and Wardwell R F 2003 Modeling relationships between use and nonuse values for surface water quality: A meta-analysis *Water Resour. Res.* **39** 1363–72

Johnston R J, Boyle K J, Adamowicz W, Bennett J, Brouwer R, Cameron T A and Vossler C A 2017 Contemporary guidance for stated preference studies *J. Assoc. Environ. Resour. Econ.* **4** 319–405

Johnston R J, Opaluch J J, Magnusson G and Mazzotta M J 2005 Who are resource nonusers and what can they tell us about nonuse values? decomposing user and nonuser willingness to pay for coastal wetland restoration *Water Resour. Res.* **41** 1–10

Kaffashi S, Shamsudin N M, Radam A, Rahim K A and Yacob M R 2013 Non-users ' trade-off between natural scenery, water quality, ecological functions and biodiversity conservation: a way to preserve wetlands *Environ. Syst. Decis.* 251–60

Kaffashi S, Shamsudin N M, Radam A, Yakob R M, Rahim A K and Yazid M 2012 Economic valuation and conservation: do people vote for better preservation of Shadegan International Wetland? *Biol. Conserv.* **150** 150–8

Kahneman D, Ritov I, Jacowitz K E, Grant P, Kahneman D, Jacowitz K E and Grant P 1993 Stated willingness to pay for public goods: a psychological perspective *Psychol. Sci.* **4** 310–5

Kahnemann D and Ritov I 1994 Determinants of stated willingness to pay for public goods: a study in the headline method *J. Risk Uncertainty* ***9–1*** 5–37

Kaushal K R and Navrud S 2018 global biodiversity costs of climate change. improving the damage assessment of species loss in integrated assessment models *Working Paper Series 4–2018* (Ås: School of Economics and Business, Norwegian University of Life Sciences)

Kerr J and Packer L 2015 Climate change impacts on bumblebees converge across continents *Science* **349** 6244

Kontogianni A, Tourkolias C, Machleras A and Skourtos M 2012 Service providing units, existence values and the valuation of endangered species: A methodological test *Ecol. Econ.* **79** 97–104

Kreye M M, Adams D C, Escobedo F J and Soto J R 2016 Does policy process in fluence public values for forest-water resource protection in Florida? *Ecol. Econ.* **129** 122–31
Kriström B and Riera P 1996 Is the income elasticity of environmental improvements less than one? *Environ. Resour. Econ.* **7** 45–55
Krutilla J V 1967 Conservation reconsidered *Am. Econ. Rev.* **57** 777–86
Krutilla J V and Fisher A C 1975 *Economics of Natural Environments* (Baltimore: Johns Hopkins University Press)
Kurz W A, Dymond C C, Stinson G, Rampley G J, Neilson E T, Carroll A L and Safranyik L 2008 Mountain pine beetle and forest carbon feedback to climate change *Nature* **452** 987
Lancaster K J 1966 A new approach to consumer theory *J. Political Econ.* **74** 132–57
Leimbach M, Kriegler E, Roming N and Schwanitz J 2017 Future growth patterns of world regions – A GDP scenario approach *Glob. Environ. Change* **42** 215–25
Leys C, Ley C, Klein O, Bernard P and Licata L 2013 Detecting outliers: do not use standard deviation around the mean, use absolute deviation around the median *J. Exp. Soc. Psychol.* **49** 764–6
Lindhjem H 2007 20 years of stated preference valuation of non-timber benefits from Fennoscandian forests: A meta-analysis *J. Forest Econ.* **12** 251–77
Logar I, Brouwer R and Paillex A 2019 Do the societal benefits of river restoration outweigh their costs? A cost- benefit analysis *J. Environ. Manage.* **232** 1075–85
Loomis J B 1996 How large is the extent of the market for public goods: evidence from a nationwide contingent valuation survey *Appl. Econ.* **28** 779–82
Loomis J, Gonzalez-caban A and Gregory R 1994 Do reminders of substitutes and budget constraints influence contingent valuation estimates? *Land Econ.* **70** 499–506
Loureiro M L and Lotade J 2005 Interviewer effects on the valuation of goods with ethical and environmental attributes *Environ. Resour. Econ.* **30** 49–72
Lundhede T, Jacobsen J B, Hanley N, Strange N and Thorsen B J 2016 Incorporating outcome uncertainty and prior outcome beliefs in stated preferences *Land Econ.* **91** 296–316
Mahieu P, Andersson H, Beaumais O, Crastes R and Wolff F (2014). Is choice experiment becoming more popular than contingent valuation? A systematic review in agriculture, environment and health. Working Papers 2014–12, French Association of Environmental and Resource Economists.
Martín-López B, Montes C and Benayas J 2008 Economic valuation of biodiversity conservation: the meaning of numbers *Conserv. Biol.* **22** 624–35
Martínez-Espiñeira R 2007 "adopt a hypothetical pup": a count data approach to the valuation of wildlife *Environ. Resour. Econ.* **37** 335–60
Mcfadden D 1994 Contingent valuation and social choice *Am. J. Agric. Econ.* **76** 689
Mcvittie A and Moran D 2010 Valuing the non-use benefits of marine conservation zone: an application to the UK marine bill *Ecol. Econ.* **70** 413–24
Mitchell R and Carson R 1989 Using Surveys to Value Public Goods: the contingent Valuation Method (Washington, DC: Resources for the Future)
Morrison M, Bennet J and Blamey R 1999 Valuing improved water qualtiy using choice modeling *Water Resour. Res.* **35** 2805–14
Morse-Jones S, Bateman I J, Kontoleon A, Ferrini S, Burgess N D and Turner R K 2012 Stated preferences for tropical wildlife conservation amongst distant beneficiaries: charisma, endemism, scope and substitution effects *Ecol. Econ.* **78** 9–18
Moser S C 2010 Communicating climate change: history, challenges, process and future directions *Wiley Interdiscip. Rev. Clim. Change* **1** 31–53
United Nations 1992 *Convention on Biological Diversity* (Nairobi. Kenya: United Nations)
Nelson J P and Kennedy P E 2009 The use (and abuse) of meta-analysis in environmental and natural resource economics: an assessment *Environ. Resour. Econ.* **42** 345–77
Newbold T and Newbold T 2018 Future effects of climate and land-use change on terrestrial vertebrate community diversity under different scenarios *Proc. R. Soc. B* **285** 2–9
Nordhaus W D and Boyer J 2000 *Warming the World: Economic Models of Global Warming* (Cambridge, Massachusetts: The MIT Press)
Nordhaus W D 2016 Revisiting the social cost of carbon *Proc. Natl Acad. Sci.* **114** 1518–23
Norton D and Hynes S 2014 Valuing the non-market benefits arising from the implementation of the EU marine strategy framework directive *Ecosyst. Serv.* **10** 84–96
Nunes P A L D and Van den Bergh J C J M 2001 Economic valuation of biodiversity: sense or nonsense? *Ecol. Econ.* **39** 203–22
O'Garra T 2009 Bequest values for marine resources: how important for indigenous bequest values for marine resources: how important for indigenous communities in less-developed economies? *Environ. Resour. Econ.* **44** 179–202
Oglethorpe D R and Miliadou D 2000 Economic valuation of the non-use attributes of a wetland - a case study for Lake Kerkini *J. Environ. Plan. Manage.* **43** 755–67
Ojea E and Loureiro M L 2011 Identifying the scope effect on a meta-analysis of biodiversity valuation studies *Resour. Energy Econ.* **33** 706–24
Pearce D W and Moran D 1994 *The Economics Value of Biodiversity* (London: Earthscan Publications)
Pearce D W and Turner R K 1990 *Economics of Natural Resources and the Environment* (Baltimore MD: Johns Hopkins University Press)
Petrolia D R, Interis M G and Hwang J 2014 America's wetland? a national survey of willingness to pay for restoration of willingness to pay for restoration of Louisana's Coastal Wetlands *Mar. Resour. Econ.* **29** 17–37
Reaves D W, Kramer R A and Holmes T P 1999 Does question format matter? Valuing an endangered species *Environ. Resour. Econ.* **14** 365–83
Richardson L and Loomis J 2009 The total economic value of threatened, endangered and rare species: an updated meta-analysis *Ecol. Econ.* **68** 1535–48
Rollins K and Lyke A 1998 The case for diminishing marginal existence values *J. Environ. Econ. Manage.* **36** 324–44
Rosenthal R 1979 The file drawer problem and tolerance for null results *Psychol. Bull.* **86** 638
Rudd M A, Andres S, Kilfoil M and Andres S 2016 Non-use economic values for little-known aquatic species at risk: comparing choice experiment results from surveys focused on species, guilds, and ecosystems *Environ. Manage.* **58** 476–90
Sanders L D, Walsh R G and Loomis J B 1990 Toward empirical estimation of the total value of protecting rivers *Water Resour. Res.* **26** 1345–57
Schaafsma M, Brouwer R, Gilbert A, van den Bergh J and Wagtendonk A 2013 Estimation of distance-decay functions to account for substitution and spatial heterogeneity in stated preference research *Land Econ.* **89** 514–37
Schaafsma M, Brouwer R and Rose J 2012 Directional heterogeneity in WTP models for environmental valuation *Ecol. Econ.* **79** 21–31
Scott C 2018 *An Economic Valuation of Biodiversity: Measuring Willingness-to-Pay for Quinoa Conservation in Peru* (San Francisco, CA: University of San Francisco.)
Shechter M, Reiser B and Zaitsev N 1998 Measuring passive use value *Environ. Resour. Econ.* **12** 457–78
Simmons J P, Nelson L D and Simonsohn U 2011 False-positive psychology: undisclosed flexibility in data collection and analysis allows presenting anything as significant *Psychol. Sci.* **22** 1359–66
Stanley T D and Doucouliagos H 2012 *Meta-regression Analysis in Economics and Business* (London: Routledge)

Stanley D L 2005 Local perception of public goods: recent assessments of willingness-to-pay for endangered species *Contemp. Econ. Policy* **23** 165–80

Stern P C, Dietz T, Abel T, Guagnano G A and Kalof L 1999 A value-belief-norm theory of support for social movements: the case of environmentalism *Human Ecol. Rev.* **6** 81–97

Sterne J A and Egger M 2001 Funnel plots for detecting bias in meta-analysis *J. Clin. Epidemiol.* **54** 1046–55

Stevens T H, Decoteau N E and Willis C E 1997 Sensitivity of contingent valuation to alternative payment schedules *Land Econ.* **73** 140–8

Subade R F and Francisco H A 2014 Do non-users value coral reefs? economic valuation of conserving Tubbataha Reefs, Philippines *Ecol. Econ.* **102** 24–32

Sutherland R J and Walsh R G 1985 Effect of distance on the preservation value of water quality *Land Econ.* **61** 281–91

Tisdell C, Wilson C and Nantha H S 2005 Policies for saving a rare Australian glider: economics and ecology *Biol. Conserv.* **123** 237–48

Tversky A and Kahneman D 1991 Loss aversion in riskless choice: a reference-dependent model author *Q. J. Econ.* **106** 1039–61

United Nations 2019 *Roadmap for Financing the 2030 Agenda for Sustainable Development 2019–2021* (New York: United Nations)

Van Prooijen A M and Sparks P 2014 Attenuating initial beliefs: increasing the acceptance of anthropogenic climate change information by reflecting on values *Risk Anal.* **34** 929–36

Veisten K, Fredrik Hoen H, Navrud S and Strand J 2004 Scope insensitivity in contingent valuation of complex environmental amenities *J. Environ. Manage.* **73** 317–31

Veisten K and Navrud S 2006 Contingent valuation and actual payment for voluntarily provided passive-use values: assessing the effect of an induced truth-telling mechanism and elicitation formats *Appl. Econ.* **38** 735–56

Wallmo K and Kosaka R 2017 Using choice models to inform large marine protected area design *Mar. Policy* **83** 111–7

Walsh R G, Loomis J B and Gillman R A 1984 Valuing option, existence, and bequest demands for wilderness *Land Econ.* **60** 14–29

Walsh R G, Bjonback R D, Aiken R A and Rosenthal D H 1990 Estimating the public benefits of protecting forest quality *J. Environ. Manage.* **30** 175–89

Waring R H, Coops N C and Running S W 2011 Predicting satellite-derived patterns of large-scale disturbances in forests of the Pacific Northwest Region in response to recent climatic variation *Remote Sens. Environ.* **115** 3554–66

Warren M S, Hill J K, Thomas J A, Asher J, Fox R, Huntley B and Thomas C D 2001 Rapid responses of British butterflies to opposing forces of climate and habitat change *Nature* **414** 65–69

White P C L, Gregory K W, Lindley P J and Richards G 1997 Economic values of threatened mammals in Britain: A case study of the otter Lutra lutra and the water vole Arvicola terrestris *Biol. Conserv.* **82** 345–54

Whitehead J C, Blomquist G C, Hoban T J and Clifford W B 1995 Assessing the validity and reliability of contingent values: a comparison of on-site users, off-site users and non-users *J. Environ. Econ. Manage.* **29** 238–51

Whitehead J, Haab T and Huang J C 2011 *Preference Data for Environmental Valuation: Combining Revealed and Stated Approaches* 1st Edition edn (New York: Routledge)

Whitehead J C and Blomquist G C 1991a A link between behavior, information, and existence value *Leisure Sci.* **13** 97–109

Whitehead J C and Blomquist G C 1991b Measuring contingent values for wetlands: effects of information about related environmental goods *Water Resour. Res.* **27** 2523–31

Willis K G and Garrod G D 1998 Biodiversity values for alternative management regimes in remote UK coniferous forests: an iterative bidding polychotomous choice approach *Environmentalist* 157–66

Willis K G, Garrod G D and Saunders C M 1995 Benefits of environmentally sensitive area policy in England: A contingent valuation assessment *J. Environ. Manage.* **44** 105–25

Windle J and Rolfe J 2005 Assessing non-use values for environmental protection of an estuary in a great barrier reef catchment *Aust. J. Environ. Manage.* **12** 147–55