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Analysis

Waters of the United States: Upgrading wetland valuation via benefit transfer☆

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ABSTRACT

With this study, we respond to the ongoing debate on the legal protection of wetlands, and the concurrent need to understand the societal benefits created by them. Using updated meta-data on wetland valuation, we illustrate how a state-of-the-art meta-regression framework that is consistent with economic theory can be adapted to generate benefit transfer predictions for incremental changes in wetland acreage over space and time. We apply this framework to estimate losses in benefits for realistic changes in wetland acreage for some sub-watersheds, as can be expected under the proposed re-definition of the "Waters of the United States" to be protected under the Clean Water Act.

1. Introduction

In 2015, the U.S. Environmental Protection Agency (EPA) and Department of the Army ("the agencies") issued the Clean Water Rule: Definition of "Waters of the United States" (CWR), which revised the definition of "Waters of the United States" (WOTUS), a foundational term establishing the jurisdictional scope of the Clean Water Act (CWA). The CWR extends CWA jurisdiction to include headwater streams and wetlands to fall under the CWA if they form a "significant nexus to downstream traditional navigable waters," which is interpreted as generally aiding in the CWA's objective to "restore and maintain the chemical, physical, and biological integrity of the Nation's waters" (U.S. Environmental Protection Agency and Department of the Army, 2015). On a case-by-case basis, this may also include isolated wetlands and bogs, such as prairie potholes, pocosins (peat bogs), and vernal pools (Wittenberg, 2017, 2018). In practice, coverage under the CWA implies that economic activities aiming to drain or fill wetlands require a permit and, potentially, compensatory mitigation efforts, for example by restoring an existing or constructing a new wetland at another suitable location (U.S. Environmental Protection Agency, 2018a,b).

However, in 2017, the agencies proposed a repeal of the CWR (U.S. Environmental Protection Agency and U.S. Department of the Army, 2017a). If the proposed rule is finalized, some of these newly non-jurisdictional wetland acres may be disturbed or developed without any corresponding wetland mitigation to offset the losses, particularly in situations where states do not maintain the previous levels of protection. The loss of these wetlands, in turn, will likely result in the loss of environmental benefits to the public at large that they would have provided.

In the 2017 proposal to recodify the definition of WOTUS, the agencies chose not to present the monetized benefits of wetland mitigation reported in their 2015 analysis due to a perceived significant uncertainty surrounding willingness to pay (wtp) to avoid wetland losses, largely related to the dated nature of the data and methods underlying the benefit estimation for wetlands given in the 2015 analysis (Boyle et al., 2017; U.S. Environmental Protection Agency and U.S. Department of the Army, 2017a).

In response, this paper provides an illustration of how recent advances in meta-analytic methods could be applied to value changes in wetland acreage regionally or nationally. Specifically, we compile an updated meta-data set on willingness to pay (wtp) to preserve or restore wetlands in the United States, drawing from 17 primary valuation studies as current as 2016. We also take advantage of recent advances in meta-regression modeling and computation of predicted benefits via the econometric framework proposed in Moeltner (2019) within the context of valuing surface water quality changes via benefit transfer (BT). Importantly, the Bayesian Nonlinear Meta-Regression Model (BNL-MRM) developed in that study satisfies fundamental theoretical properties, such as sensitivity to scope and adding-up (AU).

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The first condition stipulates that wtp should increase with the size of the resource or quality change, here "wetland acres." The AU condition, in turn, requires that total wtp to achieve target quality or acreage should be the same as the sum of incremental wtp values from reaching the environmental goal in sequential steps. The AU condition has been of central focus to MRM modelers and BT practitioners in recent years, given that many environmental policies are implemented gradually, and that the practical importance of AU is often overlooked in existing MRMs (Newbold et al., 2018; Kling and Phaneuf, 2018; Moeltner, 2019). Newbold et al. (2018) provide several examples that illustrate the importance of AU in a water quality context. In their concluding comments, the authors argue that: "*In our judgment, severe failures to comply with the adding-up condition would render a benefit transfer function unsuitable for applied policy evaluation work*" (p. 549).

In the current context, AU is an important property for any model used to predict wetland benefits, as changes in wetland acreage for a given geographic area of interest (e.g. state, county, watershed), brought forth for example by a changing legal landscape, would likely occur in increments over both space and time. Furthermore, U.S. Environmental Protection Agency and U.S. Department of the Army (2017b) issue doubts on the "theoretical consistency" of the BT exercise underlying the 2015 wetland benefit estimates as one of the main reasons for not explicitly considering these estimates in their 2017 analysis. For these reasons, we place primary emphasis on satisfying AU, at least for our benchmark model, as discussed below in more detail.

Aside from compliance with AU, the Moeltner (2019) framework brings additional computational advantages that come with a Bayesian estimation approach, such as a data-driven search algorithm to determine "optimal scope," i.e. which portions of the meta-data should be utilized for a given BT context, and to which extent. Specifically, we employ the nonlinear Stochastic Search Variable Selection (SSVS) algorithm proposed in Moeltner (2019) to examine if and to what extent the coastal/salt marsh portion of our meta-data should be allowed to influence BT results for a freshwater wetland, which is the wetland type affected by definitional changes of WOTUS and therefore the type of primary focus for this study. We find that for this data set and in contrast to Moeltner's (2019) water quality application, using only the context-specific portion of the data (here: freshwater wetlands) produces the most efficient BT predictions.

Furthermore, we exploit an additional advantage of a Bayesian estimation framework not utilized in Moeltner (2019), by comparing a set of non-nested MRMs that differ in their functional incorporation of acreage, as well as in their statistical error structure via rigorous, probability-driven criteria, to determine which of these specifications best fit the underlying data. We then use the two most promising specifications to determine optimal scope and to generate benefit predictions. We illustrate how this framework could be applied in an actual BT setting via a stylized, but realistic example.

In a nutshell, we add to the BT and valuation literature by providing the first application of a utility-theoretic, nonlinear MRM to a wetland context, using newly compiled and updated meta-data. On the econometric side, we illustrate how the Moeltner (2019) framework lends itself naturally to a probabilistic comparison of non-nested candidate MRMs, even before addressing the question of optimal scope *within* a given MRM.

2. Meta-data

As stated in the economic analysis for the proposed re-codification of WOTUS (U.S. Environmental Protection Agency and U.S. Department of the Army, 2017b, p. 8), the CWA wetland benefits in the 2015 economic analysis were derived using 22 estimates from 10 studies, published between 1986 and 2000. Given the agencies' concern regarding the dated nature of some of these sources, our primary objective in study selection was therefore to find otherwise valid contributions published since 2000. Our primary aim in terms of contributing to the existing body of wetland meta-analyses is to provide a modeling framework that satisfies the AU condition.[1]

Our meta-data are drawn from primary valuation studies, conducted in the U.S., that estimate willingness-to-pay (wtp) for changes in the acreage of wetlands that support a variety of ecosystem services including wildlife support, recreational uses (such as water fowl hunting), flood risk, and nonuse values. We ex ante included both freshwater and saltwater (coastal marshes) wetland studies, given the potential for information spillovers from saltwater to freshwater for some or all model parameters in the BT step of our analysis. Similar spillovers, or "partial pooling patterns," were observed within the context of water quality changes for rivers and lakes by Moeltner (2019), across recreational activities by Moeltner and Rosenberger (2014), and across different welfare measures by Johnston and Moeltner (2014).

The search for suitable source studies covered existing meta-analyses of wetland valuation studies (Brouwer et al., 1999; Woodward and Wui, 2001; Boyer and Polasky, 2004; Brander et al., 2006; Moeltner and Woodward, 2009), table-of-contents of environmental economics journals, keyword searches in Google and Google Scholar, and the examination of valuation databases such as the Environmental Valuation Reference Inventory (EVRI) administered by Environment and Climate Change Canada (Environment and Climate Change Canada, 2018), Oregon State University's recreation use values database (Oregan State University, 2018), and the Marine Ecosystem Services Partnership (MESP)'s valuation library (Marine Ecosystem Services Partnership, 2018).

This yielded an initial set of 24 candidate studies to provide data for the wetland meta-analysis. All studies were screened to ensure applicability and completeness of information needed to compile meta-data, such as the baseline wetland area, the extent of wetland area change, and key methodological attributes. This screening led to the exclusion of seven studies that did not provide a clear link between estimated wtp and wetland acreage (baseline and/or change). Four of the remaining 17 studies (Bauer et al., 2004; Eastern Research Group, 2016; Johnston et al., 2002; Newell and Swallow, 2013) only provided marginal wtp ("inclusive prices") for specific wetland attributes. However, all of these studies included the necessary information to derive total wtp estimates corresponding to a specific change in wetland acres as given in the respective choice experiment via separate estimation. Similarly, separate estimation steps were employed to derive policy-scenario-specific wtp estimates for Poor (1999), since the original paper aggregates welfare measures over all policy acres given in the survey. In a final step, we eliminated three observations associated with oyster reefs and mangrove habitats given in Interis and Petrolia (2016), as they were not considered relevant to this analysis.

The final meta-data includes 38 observations from 17 studies, including 58% of observations from sources published post-2000. Multiple wtp estimates are available from nine studies due to within-study variations in such attributes as wetland type (e.g., forested vs. not forested), the extent of wetland area change, and ecosystem services provided. Table 1 gives an overview of these source studies. All monetary values are adjusted to 2017 dollars.

All studies with the single exception of Awondo et al. (2011), who employ a contingent behavior travel cost model, are based on contingent valuation (yes/no decisions to obtain or avoid a "packaged" resource change at a specified bid amount) and choice experiments (first-best choice out of several specific attribute bundles, including a "price tag").[2] The data include a mix of published sources (11 journal

[1] We refer readers to Vedogbeton and Johnston (2019) for a current and comprehensive discussion of the existing meta-literature with focus on wetland valuation.

[2] Awondo et al. (2011) use a contingent behavior approach to estimate increased demand to a local beach under improved water conditions, with the

Table 1
Overview of source studies.

Author	Year	Type	Target population	Wetland type	BA	PA	WTP
Awondo et al.	2011	J	Maumee Bay SP, OH, visitors	Freshwater, unspec.	0	2499	$193
Bauer et al.	2004	J	All RI HHs	Salt marsh	11,374	11,407	$28
Bauer et al.	2004	J	All RI HHs	Salt marsh	11,343	11,407	$33
Bauer et al.	2004	J	All RI HHs	Salt marsh	11,306	11,407	$39
Bauer et al.	2004	J	All RI HHs	Salt marsh	11,272	11,407	$47
Beran, L.J.	1995	D	All SC HHs	Freshwater, forested	6000	8500	$36
Beran, L.J.	1995	D	All SC HHs	Freshwater, forested	6000	8500	$27
Beran, L.J.	1995	D	All SC HHs	Freshwater, forested	6000	8500	$33
Blomquist & Whitehead	1998	J	All KY HHs	Freshwater	3468	3968	$3
Blomquist & Whitehead	1998	J	All KY HHs	Freshwater, forested	69,580	70,080	$8
Blomquist & Whitehead	1998	J	All KY HHs	Freshwater, forested	21,716	22,216	$6
Blomquist & Whitehead	1998	J	All KY HHs	Freshwater, forested	908	1408	$19
deZoysa	1995	D	Selected MSAs, OH	Freshwater, unspec.	10,000	13,000	$109
Eastern Research Group	2016	TR	MSAs in NJ, PA, DE, MD	Salt marsh	23,860	24,860	$165
Eastern Research Group	2016	TR	MSAs in NJ, PA, DE, MD	Salt marsh	23,860	26,860	$180
Eastern Research Group	2016	TR	MSAs in NJ, PA, DE, MD	Salt marsh	23,860	28,860	$195
Interis & Petrolia	2016	J	All AL and LA HHs	Salt marsh	32,362	33,862	$179
Interis & Petrolia	2016	J	All AL and LA HHs	Salt marsh	522,667	524,167	$596
Johnston et al.	2002	J	All RI HHs	Salt marsh	11,404	11,407	$233
Johnston et al.	2002	J	All RI HHs	Salt marsh	11,402	11,407	$246
Johnston et al.	2002	J	All RI HHs	Salt marsh	11,400	11,407	$259
Johnston et al.	2002	J	All RI HHs	Salt marsh	11,398	11,407	$272
Johnston et al.	2002	J	All RI HHs	Salt marsh	11,395	11,407	$295
Kim & Petrolia	2013	J	All LA HHs	Coastal, unspec.	1,381,022	1,829,022	$658
Loomis et al.	1991	BC	All CA HHs	Freshwater, unspec.	27,000	85,000	$258
Loomis et al.	1991	BC	All CA HHs	Freshwater, unspec.	85,000	125,000	$426
MacDonald et al.	1998	J	Atlanta region, GA	Freshwater, unspec.	212,378	212,708	$108
Mullarkey & Bishop	1999	CP	All WI HHs	Freshwater, forested	219,890	220,000	$64
Newell & Swallow	2013	J	Two townships, RI	Freshwater, forested	5838	5867	$9
Newell & Swallow	2013	J	Two townships, RI	Freshwater, forested	5822	5867	$12
Newell & Swallow	2013	J	Two townships, RI	Freshwater, forested	5807	5867	$16
Petrolia et al.	2013	TR	All U.S. HHs	Coastal, unspec.	2,131,000	2,382,000	$1922
Petrolia et al.	2013	TR	All U.S. HHs	Coastal, unspec.	2,131,000	2,382,000	$998
Poor	1999	J	All NE HHs	Freshwater, unspec.	34,000	50,000	$47
Poor	1999	J	All NE HHs	Freshwater, unspec.	34,000	75,000	$42
Poor	1999	J	All NE HHs	Freshwater, unspec.	34,000	100,000	$47
Whitehead et al.	2009	J	Selected counties, MI	Freshwater, unspec.	9000	10,125	$73
Whitehead & Blomquist	1991	J	All KY HHs	Freshwater, forested	36,000	41,000	$19

BC = book chapter, CP = conference paper, D = dissertation, J = journal article, TR = technical report,
HHs = households, BA = baseline acres, PA = policy acres.

articles, one book chapter) and unpublished contributions (two dissertations, two technical reports, and one conference paper). Eight of the 17 studies have a state-wide focus in terms of their surveyed population (Bauer et al., 2004; Beran, 1995; Blomquist and Whitehead, 1998; Johnston et al., 2002; Kim and Petrolia, 2013; Mullarkey and Bishop, 1999; Loomis et al., 1991; Poor, 1999; Whitehead and Blomquist, 1991), two of them target multi-state regions (Eastern Research Group, 2016; Interis and Petrolia, 2016), five have a regional or local focus at the sub-state level (Awondo et al., 2011; de Zoysa, 1995; MacDonald et al., 1998; Newell and Swallow, 2013; Whitehead et al., 2009), and one contribution has a national scope in terms of the surveyed population (Petrolia et al., 2013).

The meta-data include 21 observations associated with freshwater wetlands. The remaining 17 cases target salt marshes or, more broadly, "coastal wetlands." Of the freshwater wetlands, 11 observations are characterized as "forested."

Based on the stipulated policy scenario to be considered by respondents, the studies in our meta-data can be grouped as follows: The first group deals with "preservation" scenarios, where existing wetlands are threatened by development, and respondents are asked about their wtp to avoid these losses in wetland acreage (Bauer et al., 2004; Beran, 1995; Blomquist and Whitehead, 1998; Kim and Petrolia, 2013; Johnston et al., 2002; Mullarkey and Bishop, 1999; Newell and Swallow, 2013; Petrolia et al., 2013; Whitehead et al., 2009; Whitehead and Blomquist, 1991). For these cases, we label the status quo, that is the higher acreage, as "policy acres," and the acreage under losses the "baseline acres," for compatibility with our econometric model, which requires a lower starting point and a higher end point for acreage.

The second group, in contrast, elicits respondents' wtp to restore areas that used to be wetlands, but have been drained to serve other current uses, to the original wetland habitat status (Awondo et al., 2011; de Zoysa, 1995; Poor, 1999; Eastern Research Group, 2016). Loomis et al. (1991) propose one restoration, and one preservation scenario to their sample of Californian households. For the restoration case, we interpret the status quo as "baseline acres," and the new status with the added (restored) wetlands as "policy acres."

The third group proposes to construct entirely new wetlands to perform various ecosystem services (Interis and Petrolia, 2016; MacDonald et al., 1998). We treat these cases analogously to the "restoration" segment in terms of defining baseline and policy acres. Also, in absence of any specific guidance from the source studies, we assume that a lack of preservation would lead to a complete and permanent loss of all ecosystem services currently flowing from the targeted wetlands. Conversely, for the restoration scenarios, we assume that the areas targeted for restoration provide zero wetland-specific ecosystem services in their altered state. Thus, the resulting wtp figures have to be

(*footnote continued*)
improvement directly related to the restoration of adjacent wetlands. Thus, the change in welfare flowing from increased/enhanced beach visits can be fully attributed to the water purification ("regulating") ecosystem function provided by the wetlands. Thus, the estimated welfare measure is not a use value for the wetlands themselves, but rather an indirect measure of their regulating benefits.

interpreted as "all-or-nothing" values, as opposed to economic benefits associated with partial or diminished services. Six studies did not provide clear numerical information on baseline or policy acres. For these cases, we used external sources and/or GIS methods to impute the missing acreage.[3]

Wetland acreages are captured in Table 1 under the "BA" (baseline) and "PA" (policy acreage) columns, respectively. The meta-data span a wide spectrum of size changes in wetland acres, from fewer than 10 acres (Johnston et al., 2002) to close to half a million (Kim and Petrolia, 2013), with commensurate large differences in baseline figures. The largest entries for both baseline and policy acreage are generally associated with studies valuing salt marshes.

The last column of the table depicts wtp estimates per household, in 2017 dollars. Nine of the included studies specify lump sum payments to obtain or prevent the stipulated change in acres, while seven others ask respondents for ongoing annual payments over an unspecified time horizon. One study, Kim and Petrolia (2013), stipulate a specific payment horizon (10 years) over which annual contributions were to be collected. Of the 17 studies, 11 used increased taxes, fees, or prices as payment vehicle, while five others proposed voluntary contributions. Newell and Swallow (2013) actually collected these voluntary contributions via real checks sent to a university-managed conservation trust fund. The wtp figure derived from Awondo et al. (2011) is to be interpreted as annual consumer surplus from additional trips taken to the area under consideration under improved environmental conditions.

Total wtp figures cover a wide range, as would be expected given the large variation in wetland acreage. At the low end, wtp is less than $20 (Blomquist and Whitehead, 1998; Newell and Swallow, 2013), while it amounts to several hundreds of dollars for other studies, most of which propose large size changes in wetland acreage over a large geographic area (e.g. Kim and Petrolia, 2013; Loomis et al., 1991; Petrolia et al., 2013). On a per-acre basis, Johnston et al. (2002) produce by far the largest values for their valuation study of coastal marshes, between $25 and $78 per acre, while all other observations remain well below $1/acre restored or preserved. However, given our primary focus on freshwater wetlands, and to avoid a further reduction in our already modest sample size, we opt to retain these observations in our combined freshwater/saltwater model below.[4]

Table 2 lists the variables included in our analysis and provides summary statistics by wetland type (freshwater and coastal), and for the sample at large. We use the natural log of wtp, in 2017 dollars, as dependent variable in all our specifications. As in Moeltner (2019), we group the explanatory variables into two categories: "moderators," and "context-specific." "Moderators" include variables that characterize the payment mechanism, such as `volunt` and `lumpsum`, elicitation format (`ce` for "choice experiment"), publication type (`nrev` for "not peer-reviewed"), and `median`, capturing if wtp is reported as a sample median, rather than a mean (18% of observations). Although these variables are not directly relevant for the policy context, they need to be included in the meta-model to avoid omitted variable problems (see e.g. Johnston et al., 2017, 2006b; Moeltner et al., 2007).

In contrast, "context-specific" variables are those that would generally receive a specific value for a given policy site in a BT context. As is evident from the table, this group includes `lnyear`, the log of the year data were collected for a given study, relative to the oldest data collection year in the data (1988).[5] This time index, also used, inter alia, in Johnston et al. (2017), Newbold et al. (2018) and Johnston et al. (2019) in the context of valuing changes in water quality, captures a potential trend in preferences and/or advances in (unobserved) survey methodology. We also include in this category `lnincome`, the log of income for a specific study's target population in 2017 dollars. For some studies, income had to be imputed using census information due to the absence of reported sample-specific figures. As is clear from the table, freshwater studies tend to be slightly older than coastal applications, but income figures are comparable across the two groups.

Geographic indicators include "South-Atlantic/Gulf States" `sagulf`, "New England/Mid-Atlantic States" `nema`, and "North/Midwestern States" `nmw`, each of which refers to the states shown in the second column of the table. Thus, the implicit geographic benchmark absorbed by the constant term of the regression is the national study by Petrolia et al. (2013) and the California study by Loomis et al. (1991). Since local residents may place a greater value on nearby wetlands than a broader constituency, we also add spatial variable `local` to flag observations associated with a local or sub-state target population. This variable serves as a proxy to what has been labeled as "distance decay" of wtp in the existing literature (e.g. Bateman et al., 2006; Schaafsma, 2015; Johnston et al., 2017). The importance of this spatial distinction is confirmed by our empirical estimates, discussed below.

In general, the geographic scope and the extent of the market underlying the coastal studies differ from the freshwater wetland studies. Specifically, coastal studies tend to be primarily located in the New England/Mid-Atlantic region, and all of them target a broader, regional population. In contrast, freshwater wetland studies are more diverse geographically and target both local and regional populations.

Wetland service indicators include `prov`, for "provisioning" (e.g. fishing, hunting), `reg`, for "regulating" (e.g. water filtration, flood control), and `cult`, for "cultural" (e.g. non-extractive recreation). The fourth typical wetland service of "supporting" (e.g. habitat, nursery) applies to all but one observation in the meta-data, and can thus not be explicitly included in the regression model.[6] As is evident from the table, "provisioning" is a more predominant function for coastal applications (82% of observations) than freshwater wetlands (24% of observations). The nature of provisioning services provided by salt marshes and freshwater wetlands also differs. Salt water marshes support shellfishing, hunting, and fishing, while freshwater wetlands are primarily used for waterfowl hunting.

The binary indicator `forest` specifies if the wetland was described to respondents as "forested." There are no forested coastal wetlands included in our final meta-data. Our settings for baseline (`q0`) and policy acres (`q1`) round off the context-specific group of explanatory variables. As pointed out earlier, coastal applications generally show figures for baseline and policy acres that exceed those for freshwater studies by an order of magnitude. As we show below, these significant differences in context-specific attributes between coastal and freshwater studies make it problematic to pool the two data segments for joint analysis.

Given the small sample size and sparse composition of our data, not

[3] For Awondo et al. (2011), the sketched map of the research area given in that paper was used to estimate policy acres. For Bauer et al. (2004), the approximate acreage for salt marshes in RI at the time of data collection extracted form the National Land Cover Database (NLCD) was uses as policy endpoint, and that figure minus the stipulated acres to be preserved as the baseline. The same applies to Johnston et al. (2002). For Kim and Petrolia (2013), we imputed the total acres of saltwater wetlands in coastal parishes as policy acres, and that minus the stipulated acres at stake as baseline. For Newell and Swallow (2013), the estimated acreage of vegetated wetlands for the two townships considered in that study was used as policy endpoint, and that figure minus the proposed acreage subject to preservation as baseline. Similarly, the total estimated acreage of freshwater wetlands in the watershed considered by MacDonald et al. (1998) was used as baseline wetland area.

[4] As a robustness check, we estimate our combined meta-model (labeled "SSVS model" below) without the five Johnston et al. (2002) observations. This largely leaves results for key parameters unchanged, but poses considerable identification problems due to the diminished sample size.

[5] We add "1" to this number to avoid taking a log of zero for the oldest study in our data.

[6] The single exception is Whitehead et al. (2009), who did not incorporate a description of wetland services in their survey.

Table 2
Variable description and sample statistics.

	Description	Freshwater			Coastal			All		
		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Dependent variable										
lnwtp	log(total wtp in 2017 dollars)	3.56	1.05	6.06	5.31	3.32	7.56	4.34	1.05	7.56
Context-specific										
lnyear	log(year of data collection - oldest year +1)	1.57	0.00	2.89	2.78	2.20	3.30	2.11	0.00	3.30
lninc	log(income in 2017 dollars)	10.97	10.64	11.48	11.04	10.73	11.42	11.00	10.64	11.48
sagulf	1 = S-Atlantic/Gulf (AL,GA,SC,LA)	0.19	0.00	1.00	0.18	0.00	1.00	0.18	0.00	1.00
nema	1 = NE/mid-Atlantic,(DE,MD,NJ,PA,RI)	0.14	0.00	1.00	0.71	0.00	1.00	0.39	0.00	1.00
nmw	N/Mid-West (KY,MI,NE,OH,WI)	0.57	0.00	1.00	0.00	0.00	0.00	0.32	0.00	1.00
local	1 = target population at sub-state level	0.33	0.00	1.00	0.00	0.00	0.00	0.18	0.00	1.00
prov	1 = provisioning function affected	0.24	0.00	1.00	0.82	0.00	1.00	0.50	0.00	1.00
reg	1 = regulating function affected	0.52	0.00	1.00	0.76	0.00	1.00	0.63	0.00	1.00
cult	1 = cultural function affected	0.76	0.00	1.00	0.76	0.00	1.00	0.76	0.00	1.00
Forest	1 = forested wetland	0.52	0.00	1.00	0.00	0.00	0.00	0.29	0.00	1.00
q0	Baseline acres (1000s)	40	0	220	375	11	2131	190	0	2131
q1	Policy acres (1000s)	51	1	220	431	11	2382	221	1	2382
q0,alt	Alternative baseline acres (1000s)	29	0	220	371	0	2131	182	0	2131
q1,alt	Alternative policy acres (1000s)	40	0	220	428	0	2382	214	0.003	2382
Moderators										
volunt	1 = payment mechanism = voluntary contribution	0.43	0.00	1.00	0.00	0.00	0.00	0.24	0.00	1.00
Lumpsum	1 = payment frequency = lump sum (single payment)	0.43	0.00	1.00	0.47	0.00	1.00	0.45	0.00	1.00
ce	1 = elicitation method = choice experiment	0.14	0.00	1.00	0.88	0.00	1.00	0.47	0.00	1.00
nrev	1 = study was not peer-reviewed	0.24	0.00	1.00	0.24	0.00	1.00	0.24	0.00	1.00
Median	1 = wtp estimate = median	0.33	0.00	1.00	0.00	0.00	0.00	0.18	0.00	1.00

Std = standard deviation, Min = minimum, Max = maximum
NE = New England, N = North.

all coefficients for the variables listed in Table 2 are identified in a single regression model. While there are many different subsets of identified regressors, we use the following guidelines for the choice of variables to be included in the MRM: (i) use as many relevant context-specific variables as possible, and (ii), of the moderator variables, give priority to `volunt` and `lumpsum`, as these two are likely to have the strongest effect on wtp among this group (e.g. Johnston et al., 2017).

The resulting identified coefficients are listed in Table 3, for the full meta-data, the freshwater-only data, and the salt/coastal wetland-only portion, respectively. While all variables described above have identified coefficients for the full model, we have to restrict the set of moderator variables to `volunt` and `lumpsum` for the freshwater subset. For the saltwater portion, only the context-specific coefficients for the spatial indicator `nema` and the wetland service indicator `cult` are identified, in addition to year, income, and acres. Similarly, only coefficients of `lumpsum` and `nrev` are identified in the moderator group.

Table 3
Parameter identification.

	Identified parameters		
	Full	Fresh	Salt
Context-specific			
lnyear	x	x	x
lninc	x	x	x
sagulf	x	x	–
nema	x	x	x
nmw	x	x	–
Local	x	x	–
prov	x	x	–
reg	x	x	–
cult	x	x	x
Forest	x	x	–
q0	x	x	x
q1	x	x	x
Moderators			
volunt	x	x	–
Lumpsum	x	x	x
ce	x	–	–
nrev	x	–	x
Median	x	–	–
Observations	38	21	17
Studies	17	11	6

Full = full meta-data.
Fresh = freshwater wetlands only.
Salt = salt marshes/coastal wetlands only.

These restrictions will affect our ability to borrow from the salt marsh/coastal portion to inform freshwater BT predictions. While we can ex ante allow for saltwater-specific interaction terms for the six identified context-specific coefficients, we have to implicitly assume pooling of fresh- and saltwater data on the remaining six coefficients. As discussed below in more detail, this leads to a sub-optimal performance of a partially pooled model compared to the freshwater-only model.

3. Econometric model

3.1. Nonlinear meta-regression models

As a starting point for our analysis, we adopt the Bayesian Nonlinear Meta-regression Model (BNL-MRM) developed in Moeltner (2019). This model has the desirable property of satisfying AU by design with a relatively sparse and simple specification. In other words, BT predictions flowing from this model for, say, a change from the baseline quantity (of acres) q_0 to target or "policy" quantity q_1 will always be numerically equal, regardless of the number of increments with which the overall change may be implemented in reality.

Within this "adding-up compliant" family of models, we consider three sub-specifications that differ in how we model the variance of the unobservable model components ("error term"). For observation i reported in study s, our most general version of the BNL-MRM, used in Moeltner (2019) and henceforth referred to as model M1a, can be written as:

$$y_{is} = \mathbf{x}'_{is}\boldsymbol{\beta} + \log(\gamma^{-1}(\exp(\gamma q_{1,is}) - \exp(\gamma q_{0,is}))) + u_s + \epsilon_{is}, \quad \text{with}$$
$$u_s \sim n(0, \sigma_u^2),$$
$$\epsilon_{is} \sim n(0, \sigma_\epsilon^2 \omega_{is}), \quad \text{where} \quad \omega_{is} \sim ig\left(\frac{\nu}{2}, \frac{\nu}{2}\right) \tag{1}$$

That is, logged wtp, y_{is}, is a linear function of observation and/or study-specific regressors $\mathbf{x}_{is}$, including a constant term and logged income, a nonlinear component involving baseline and target (policy) wetland acres with corresponding quantity parameter γ, a study-specific, normally distributed random effect u_s, and an observation-level error term ϵ_{is}.

As shown in Eq. (1), the idiosyncratic error ϵ_{is} is normally distributed with observation-specific variance $\sigma_\epsilon^2 \omega_{is}$, where weight ω_{is} follows an inverse-gamma density with shape and scale equal to $\frac{\nu}{2}$.[7] Thus, in addition to allowing for nonlinearity in quality, our specification follows recommended practices in meta-regression modeling by leaving room for unobserved study-level heterogeneity and observation-level heteroskedasticity (e.g. Rosenberger and Loomis, 2000; Johnston et al., 2006a; Moeltner et al., 2007; Johnston and Rosenberger, 2010).

At the study-panel level, the M1a model can be expressed as:

$$\mathbf{y}_s = \mathbf{X}_s\boldsymbol{\beta} + \log(\gamma^{-1}(\exp(\gamma \mathbf{q}_{1,s}) - \exp(\gamma \mathbf{q}_{0,s}))) + \mathbf{i}_s u_s + \boldsymbol{\epsilon}_s, \quad \text{with}$$
$$\mathbf{i}_s u_s \sim n(\mathbf{0}, \sigma_u^2 \mathbf{I}_s),$$
$$\boldsymbol{\epsilon}_s \sim n(\mathbf{0}, \sigma_\epsilon^2 \boldsymbol{\Omega}_s), \quad \text{and} \quad \boldsymbol{\Omega}_s = \begin{bmatrix} \omega_{1s} & 0 & \dots & 0 \\ 0 & \omega_{2s} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & \omega_{n_s,s} \end{bmatrix}, \tag{2}$$

where n_s is the panel size for study s, $\mathbf{i}_s$ is a vector of ones of length n_s, $\mathbf{I}$ is an identity matrix of dimension s, and the $\mathbf{q}$ vectors collect acreage settings for all n_s observations.

Model M1b differs from M1 by eliminating the heteroskedastic property of the error term, while preserving random study effects. At the study-panel level it is given as:

$$\mathbf{y}_s = \mathbf{X}_s\boldsymbol{\beta} + \log(\gamma^{-1}(\exp(\gamma \mathbf{q}_{1,s}) - \exp(\gamma \mathbf{q}_{0,s}))) + \mathbf{i}_s u_s + \boldsymbol{\epsilon}_s, \quad \text{with}$$
$$\mathbf{i}_s u_s \sim n(\mathbf{0}, \sigma_u^2 \mathbf{I}_s), \quad \boldsymbol{\epsilon}_s \sim n(\mathbf{0}, \sigma_\epsilon^2 \mathbf{I}_s). \tag{3}$$

Our third model, model M1c, drops the within-study effect and stipulates spherical idiosyncratic errors, as is typical for standard regression models. It thus reduces to:

$$\mathbf{y}_s = \mathbf{X}_s\boldsymbol{\beta} + \log(\gamma^{-1}(\exp(\gamma \mathbf{q}_{1,s}) - \exp(\gamma \mathbf{q}_{0,s}))) + \boldsymbol{\epsilon}_s, \quad \text{with}$$
$$\boldsymbol{\epsilon}_s \sim n(\mathbf{0}, \sigma_\epsilon^2 \mathbf{I}_s). \tag{4}$$

3.2. Linear meta-regression models

The majority of existing meta-analyses of wetland valuation (or related contexts with changes in quality or acreage) have used linear MRMs (e.g. Brouwer et al., 1999; Brander et al., 2007; Moeltner and Woodward, 2009; Vedogbeton and Johnston, 2019). To compare performance of linear and nonlinear MRMs, we also consider two linear-in-acreage MRMs for both estimation and BT predictions. The first, labeled MRM1-linlin in Moeltner (2019), is shown in that study to exhibit the best fit with the underlying meta-data, but produces severe AU-violations for welfare estimates. In contrast, the second linear model, referred to as MRM2 in Moeltner (2019), emerges as less probable to have generated the underlying data, but performs well in terms of AU properties in the prediction stage.

Using notation from above, the MRM1-linlin at the panel level and with the most general error structure is given as:

$$\mathbf{y}_s = \mathbf{X}_s\boldsymbol{\beta} + \gamma_0 \mathbf{q}_{0,s} + \gamma_\Delta(\mathbf{q}_{1,s} - \mathbf{q}_{0,s}) + \mathbf{i}_s u_s + \boldsymbol{\epsilon}_s, \tag{5}$$

where the error component properties are as for the BNL-MRM. Thus, it relates logged wtp to both baseline size and change in acreage, with both terms entering in linear fashion on the right hand side.

The MRM2, in turn, is given as:

$$\mathbf{y}_s - \log(\mathbf{q}_{1,s} - \mathbf{q}_{0,s}) = \mathbf{X}_s\boldsymbol{\beta} + \gamma\left(\frac{\mathbf{q}_{0,s} + \mathbf{q}_{1,s}}{2}\right) + \mathbf{i}_s u_s + \boldsymbol{\epsilon}_s, \tag{6}$$

thus relating logged per-acre-wtp over the range of the stipulated change to the midpoint of this range on the right hand side.

For each linear model, we ex ante consider all three error versions, as described above for the BNL-MRM. For consistent labeling, we will henceforth refer to the MRM1-linlin framework as "M2", with sub-models M2a (heteroskedasticity and random effects), M2b (random effects only), and M2c (idiosyncratic error). Analogously, we will label the three sub-specifications of the MRM2 as M3a through M3c in the remainder of this text.

3.3. Model comparison

As mentioned above, one advantage of our Bayesian estimation framework is that it allows for a rigorous, probability-based comparison of these non-nested models via posterior model probabilities and Bayes Factors (BFs) (Kass and Raftery, 1995). While the specifications with the most complete specification for error components follow best practices in meta-modeling, it is possible that the less complex versions might receive higher posterior probability due to their sparser set of parameters, especially given our small sample size.

As discussed in Kass and Raftery (1995), Koop (2003), and Koop (2007), among others, BFs are relative posterior probabilities of one model over another. They signal the relative fit with actual data of two competing models, with respect to both their stipulated priors and chosen likelihood function. They are widely considered a probability-theoretic and rigorous form of model comparison. Our strategy is to first compare the three sub-specifications within each general modeling framework (M1, M2, M3), and then peg the "winners" of each set against each other (i.e. best of M1, best of M2, best of M3).

All nine models are estimated via Bayesian posterior simulation based on Gibbs Sampling. We choose the same prior distributions as Moeltner (2019), that is normal for $\boldsymbol{\beta}$ and γ, inverse-gamma for σ_ϵ^2 and σ_u^2, and gamma for ν. Moeltner (2019) also gives details on the likelihood function, the resulting kernel of the joint posterior distribution, and the Gibbs Sampler (GS) to estimate models M1a, M2a, and M3a. The respective GS's for models M1b, M2b, and M3b follow this pattern, with omitted steps for draws of ν. Models M1c, M2c, and M3c additionally drop steps for draws of σ_u^2 and the random effects $u_s, s = 1 \dots S$.

3.4. Stochastic search pooling model for benefit transfer

Given our primary focus on freshwater wetlands, we first estimate all model versions using the freshwater-only data to obtain coefficients suitable for a freshwater-specific BT scenario.

However, this requires discarding the 11 salt marsh/coastal wetland data points, a loss of 29% of the overall data. As argued in Moeltner and Rosenberger (2008), Moeltner and Rosenberger (2014), Johnston and Moeltner (2014), and Moeltner (2019), this would be akin to discarding relevant information if the two contexts, here freshwater wetlands and saltwater wetlands, share pooled coefficients for all or a sub-set of regressors. In our case, for example, it is ex ante feasible that the `lnyear` and/or `lnincome` effects are similar for both wetland types, as public preferences for wetland conservation may be trending in similar fashion for both wetland habitats. The marginal effect of income on wtp, which

[7] As discussed in Geweke (1993), this hierarchical specification of the variance of ϵ_{is} is equivalent to drawing the error term from a t-location-scale distribution with mean zero, scale σ_ϵ^2, and ν degrees of freedom (implying a variance of $\sigma_\epsilon^2 \frac{\nu}{\nu - 2}$). This allows for a higher probability of larger error variances than would be expected for a basic normal model, a likely occurrence in any meta-regression context with a diverse set of underlying source studies.

is directly related to the marginal utility of income as shown in Moeltner (2019), should also be largely invariant to wetland type.

The studies cited above propose various Bayesian search algorithms to determine if such pooling patterns exist, and if exploiting these patters enhances the efficiency of BT predictions. Here, we adopt the Stochastic Search Variable Selection (SSVS) algorithm originally developed by George and McCulloch (1993) and used in Moeltner (2019), as it is the most compatible with the nonlinear specification of the meta-regression for our M1-family of models.

As shown in Moeltner (2019), the SSVS procedure is implemented by allowing for interaction terms of context-specific variables with an indicator for the ancillary context, here "saltwater wetlands." Specifically, using our M1a specification as an example, we re-write the model in Eq. (2) as:

$$\begin{aligned}\mathbf{y}_s = \; & \mathbf{X}_{1s}\boldsymbol{\beta}_x + \mathbf{M}_s\boldsymbol{\beta}_m + \mathbf{Z}_s\boldsymbol{\delta} \\ & + \log((\gamma + \delta_\gamma \mathbf{d}_s)^{-1}(\exp((\gamma + \delta_\gamma \mathbf{d}_s)\mathbf{q}_{1,s}) - \exp((\gamma + \delta_\gamma \mathbf{d}_s)\mathbf{q}_{0,s}))) \\ & + \mathbf{i}_s u_s + \epsilon_s,\end{aligned} \tag{7}$$

where data matrix $\mathbf{X}_{1s}$ collects all context-specific variables shown in Table 3, while $\mathbf{M}_s$ includes the moderator variables that are identified for the freshwater context, i.e. `lumpsum` and `volunt`. Matrix $\mathbf{Z}_s$ in Eq. (7) comprises all identified interactions of the variables in $\mathbf{X}_{1s}$ with the saltwater context, i.e. `lnyear`, `lninc`, `nema`, `cult`, `q0`, and `q1`, as discussed above. Similarly, we allow for a deviation δ_γ for the quality parameter for saltwater contexts, characterized by indicator vector $\mathbf{d}_s$, in the nonlinear portion of the model, as is evident from the second line in Eq. (7).

At every iteration of the GS, the SSVS algorithm decides if an element of the deviation vector $\boldsymbol{\delta}$ is essentially zero – indicating that freshwater and saltwater contexts pool along that particular dimension – or not. The same holds for quality deviation parameter δ_γ. As shown in Moeltner (2019), this is accomplished via a mixture prior for all deviation terms, and a corresponding indicator vector for nonzero interactions that is updated at every iteration of the GS. Upon convergence of the sampler, the analyst can then inspect how often a given deviation term was deemed "important" or "superfluous" by the algorithm, and draw corresponding modeling inference. As shown in Moeltner (2019), this "controlled" pooling strategy via SSVS can lead to substantial efficiency gains for the welfare predictions of interest.

The SSVS method proceeds in analogous fashion for models M1b and M1c by imposing the error structure as given in Eq. (3) for M1b, and in Eq. (4) for M1c. The SSVS framework is conceptually the same for the linear models (M2, M3 families), though there is no need to estimate a separate deviation term for the acreage parameter, as acre-related variables are incorporated in the linear data portion $\mathbf{X}_{1s}$, with corresponding interaction terms collected in $\mathbf{Z}_s$.

3.5. BT predictions

To obtain BT predictions for both the freshwater wetlands-only and the SSVS model (using the full meta-data and saltwater interaction terms), we first compute logged wtp y_p for a given draw of β_x and β_m from the GS and specific policy setting, as reflected by policy-specific regressor vector $\mathbf{x}_p$ and quality settings $q_{0,p}$ and $q_{1,p}$, respectively. Using again model M1a as example, this implies:

$$\hat{y}_p = \mathbf{x}_p'\boldsymbol{\beta}_x + \log(\gamma^{-1}(\exp(\gamma q_{1,p}) - \exp(\gamma q_{0,p}))) + \sum_{t=1}^{T} w\, \mathbf{m}_t'\boldsymbol{\beta}_m + u + \epsilon, \tag{8}$$

where u and ϵ are drawn from their respective distributions, as applicable depending on model. To neutralize the effect of moderator variables, which are de facto "nuisance terms" with respect to policy-focused predictions, we follow Moeltner et al. (2007), Moeltner and Rosenberger (2008), and Moeltner (2019) and average our predictions over all T permissible combinations of moderator vector $\mathbf{m}$, with each combination receiving equal weight of $w = 1/T$.

We compute $\hat{y}_p$ for each draw of model parameters flowing from the GS, and then exponentiate these draws to obtain the dollar-valued posterior predictive distribution (PPD) of wtp for a specific change in wetland acreage. We then examine these PPDs for a sequence of stepwise size changes to illustrate compliance with the adding-up property. Benefit transfer predictions for all other models are obtained in analogous fashion by adjusting the error components and/or the functional form of the predictive equation accordingly.

4. Estimation results

Following Moeltner (2019), we set all normal priors to have a mean of zero and a variance of ten, and all inverse-gamma priors to have shape and scale equal to 1/2. The scale parameter for the gamma prior of ν, ν_0, is set to ten as well. These are extremely vague priors that place the bulk of informational burden on the data, as desired.

As discussed in Moeltner (2019) draws of ν (for all models with heteroskedasticity) and γ (for all nonlinear models) require Metropolis-Hastings (MH) steps within the Bayesian posterior simulator (GS). We chose all corresponding tuning parameters to achieve an acceptance rate in the 40–50 % range, as recommended in Gelman et al. (2004). For all nonlinear models, we use one million burn-ins and an equal amount of "keepers" to assure that the sampler achieved convergence to the joint posterior. We then choose every tenth draw for inference to reduce autocorrelation across retained draws. For linear models, we found it sufficient to use 10,000 burn-ins and 100,000 retained draws, as autocorrelation and thus the need for thinning the posterior sequence was not a first-order concern for those specifications.

In all cases, we use Geweke's (1992) split-mean diagnostics to assess convergence. Bayes Factors for model comparison are derived using the methods described in Chib and Jeliazkov (2001) for all models with MH steps, and the approach outlined in Chib (1995) for all other specifications.

4.1. Freshwater-only model

Results for the freshwater-only meta-regression for all nine model specifications, grouped by model type, are given in the online appendix. As shown there, within the M1 group, the simplest version M1c (with idiosyncratic errors) receives the strongest support as measured via BFs. In contrast, the most general version M2a exhibits the highest posterior probability within the M2 group. For the M3-type models, BFs favored again the simplest version, M3c. It should be noted that M1c and M3c also receive the highest model probabilities in absolute terms across all nine models.

Results for the most promising version within each model category are given in Table 4. For each model, the table gives the posterior mean, posterior standard deviation, and the proportion of the posterior distribution to the right of zero ($p > 0$). The latter statistic provides an at-a-glance assessment if a given variable's effect on outcome is predominantly positive ($p > 0$ is close to 1), negative ($p > 0$ is close to 0), or ambiguous ($p > 0$ is close to 0.5). The more posterior mass to one or other side of zero, the clearer is the signal for the direction of the marginal effect of the corresponding coefficient.

The bottom of Table 4 shows the logged marginal likelihood, a Bayesian measure of model fit, and the BF of the overall best-fitting specification, here M3c, over the other two versions. Mathematically, these BFs are computed as the exponentiated difference of the corresponding logged marginal likelihoods. Based on these statistics it is immediately obvious that the nonlinear model M1c and the linear model M3c are essentially equally likely to have generated the underlying data, with a pairwise BF of close to one, while linear model M2a with both baseline acreage and change in size captured on the right hand side is far less probable to fit these specific meta-data (BF (M3c/

Table 4
Estimation results for top models, freshwater data.

	M1c			M2a			M3c		
	Mean	Std.	$p(>0)$	Mean	Std.	$p(>0)$	Mean	Std.	$p(>0)$
Constant	−0.546	3.097	0.430	−0.166	3.128	0.478	−0.527	3.107	0.432
Context-specific									
lnyear	−0.359	0.667	0.281	0.425	0.950	0.685	−0.344	0.675	0.292
lninc	0.211	0.363	0.723	0.345	0.367	0.828	0.205	0.365	0.714
sagulf	−0.406	1.743	0.405	−0.390	1.961	0.418	−0.395	1.741	0.408
nema	−0.784	1.538	0.295	−3.922	2.020	0.036	−0.756	1.556	0.303
nmw	−1.073	1.556	0.244	−0.518	1.737	0.379	−1.059	1.558	0.248
Local	3.130	0.895	0.999	0.333	1.311	0.606	3.100	0.916	0.999
prov	−2.273	0.876	0.009	0.456	1.397	0.640	−2.256	0.883	0.009
reg	1.632	0.850	0.970	−0.947	1.234	0.208	1.617	0.851	0.969
cult	−0.317	1.563	0.413	1.100	1.713	0.746	−0.278	1.580	0.425
Forest	1.118	0.726	0.937	0.824	0.728	0.883	1.107	0.730	0.934
Moderators									
volunt	−0.016	1.038	0.495	−1.666	1.347	0.104	−0.015	1.035	0.496
Lumpsum	1.486	0.771	0.968	−0.170	1.142	0.440	1.472	0.774	0.967
γ	0.008	0.007	0.883	–	–	–	–	–	–
q0	–	–	–	0.002	0.008	0.600	–	–	–
q1-q0	–	–	–	0.001	0.016	0.516	–	–	–
(q0+q1)/2	–	–	–	–	–	–	0.009	0.007	0.884
σ_ε^2	0.474	0.260	1.000	0.287	0.183	1.000	0.474	0.260	1.000
σ_μ^2	–	–	–	1.562	2.279	1.000	–	–	–
ν	–	–	–	13.741	10.424	1.000	–	–	–
Combined variance	–	–	–	1.898			0.474		
log mlh	−49.342			−51.586			−49.249		
BF(M3c/other)	1.098			9.429					

Mean = posterior mean, Std. = posterior standard deviation.
prob(> 0) = share of posterior density to the right of zero.
log mlh = log marginal likelihood.
BF = Bayes Factor.

M2a) = 9.4). It also exhibits a much larger combined error variance (1.9 vs. 0.47). In other words, the by far best-fitting model in Moeltner (2019) is clearly inferior to the best nonlinear-in-acres version (M1c) and the best version with the log of average wtp as the dependent variable (M3c) for our application. This stresses the importance of viewing these model comparisons as strictly application-specific, with potentially large changes in relative model probabilities for competing versions across different contexts and data sets. Due to its poor fit with the underlying data relative to the other two specifications, we will rule out M2a (and thus the entire M2-group) as a viable candidate for BT, and henceforth consider only the two remaining models M1c and M3c.

Since M1c and M3c also generate close to identical posterior results for shared parameters, we will focus our discussion of parameter estimates on the nonlinear version M1c, shown in the first set of columns in Table 4. Based on the $p(>0)$ metric, among context-specific regressors the strongest signals for an unambiguously signed effect on wtp are issued by `local`, `reg`, `forest`, and `prov`, all of which have over 90% of probability mass on one side of zero. They also exhibit the largest posterior means, in absolute terms. Specifically, wetland values elicited within a local context exceed non-local values by a factor of 21.9 (exp (3.130) − 1 = 21.9). Similarly, wetlands that offer regulatory services (water purification, flood control) are valued over four times more (exp (1.632) − 1 = 4.1) than wetlands that do not fulfill these functions. Similarly, benefits provided by forested wetlands, captured by indicator `forest`, generate wtp values that exceed those associated with non-forested wetlands by a factor of 2.1 (exp(1.118) − 1 = 2.1). In contrast, the negative effect of `prov` is somewhat unexpected. Taking the posterior mean of −2.273 at face value, it implies that wetlands that also provide extractive recreational opportunities (fishing, hunting) generate wtp that is close to 90% lower (exp(−2.273) − 1 = −0.9) than wtp for wetlands without extractive services. While this may well be an artifact of our small sample, potentially masking an unobserved confounding effect, it may be possible that respondents prefer to preserve or restore wetlands as a place for "nature to do its work," without any human harvesting of resources.[8]

Other context-specific variables with at least 70% of probability mass on either side of zero include `lnyear`, `lninc`, `nema`, and `nmw`. Thus, our results provide indication of *modest strength* that wetland values have declined slightly over time at a rate of 0.4% per year since 1988. As expected, income has a positive effect on wtp with an elasticity of approximately 0.2%. In terms of regional effects, compared to our implicit default category (national plus California), wtp is approximately 54% (exp(−0.784) − 1 = −0.54) lower in the New England/Mid-Atlantic region, and 66% (exp(−1.073) − 1 = −0.66) lower in the North/Mid-western states region. To some extent this may point at the increased spatial density of wetlands, and thus available substitutes, in those regions compared to the default geographic locations.

The freshwater model also produces a significant moderator variable, `lumpsum`. Specifically, hypothetical contributions collected via a single payment are, on average 340% higher (exp(1.486) − 1 = 3.4), than for funding scenarios that stipulate recurring annual payments. This is consistent with economic theory, as respondents can be expected to compare the stipulated lump sum bid to the net present value of all future services flowing from the proposed wetland preservation or restoration project. Given positive discounting, this should be a larger figure than the corresponding annualized service values.

[8] Naturally, a richer model based on a larger sample would allow for interaction terms across wetland services, as it is well possible that respondents value these services in bundles, rather than in isolation. Along the same lines, an interaction of `prov` with `local` might be revealing, as local constituents may place a larger value on extractive use at nearby wetlands than a broader community of primarily non-users. However, this is not possible with our sparse data as it includes only a single observation that takes a value of one for such an interaction term.

The posterior distribution of the acreage parameter γ for M1c is largely positive, implying a convex wtp function (see Moeltner, 2019), albeit with slight curvature given the small numerical magnitude of this parameter. The same holds for M3c, where a positive midpoint parameter (here 0.009) also implies convexity. As discussed in Moeltner (2019), convexity of the wtp function is not ruled out by economic theory. In our case, for example, it is possible that certain wetland services (e.g. flood risk reduction and supporting services) only "kick in" or compound synergistically with increasing acreage, leading in turn to marginally increasing values. However, as we discuss below in more detail, we find that due to this convexity property predictions flowing from *either model* become unreasonably large (and increasingly imprecise) if either baseline or policy acres lie far outside the acreage range of the underlying meta-data. Aside from this *practical* caveat related to curvature, both models satisfy sensitivity to scope (M1c for any value of γ, M3c for $\gamma > -2/(q_1 - q_0)$). As shown below, both also satisfy AU, M1c by construction, and M3c on empirical grounds.

4.2. SSVS model

SSVS results for the two best-fitting models M1c and M3c are given in the online appendix. Recall that these data-augmented models always include all variables identified for the freshwater context (see Table 3), but determine heuristically if the (identified) interaction terms for the saltwater context should be included or not at each iteration of the GS. Importantly, only the variables identified for freshwater wetlands, including all context-specific regressors listed in Table 3, plus moderators `volunt` and `lumpsum`, will be used to generate predictions for the actual BT exercise. The primary role of the saltwater interaction terms is to modify the freshwater coefficients when the interaction terms are deemed important enough to be included by the search algorithm. If this happens often enough, it will probably be inefficient to "drag along" the saltwater data, as this provides evidence that coefficients do not pool along the identified interactive dimensions. In other words, if interaction terms receive high posterior inclusion probabilities, it will likely be more efficient to base BT predictions on the freshwater data alone, using the results from Table 4. On the contrary, if posterior inclusion probabilities are low, the output from the SSVS routine may generate tighter BT results due to the increased sample size, as clearly illustrated in Moeltner (2019) for the case of water quality changes at rivers and lakes.

A serious shortcoming for using the SSVS approach for the current application and across all considered models is that only a limited number of context-specific interaction terms are identified (i.e. `lnyear`, `lninc`, `nema`, `cult`, and baseline and policy acreage). For the remaining variables (i.e. `sagulf`, `nmw`, `local`, `prov`, `reg`, and `forest`), perfect pooling of freshwater and saltwater coefficients has to be assumed by default. This "forced pooling" may be unwarranted and will produce misleading results if the true impact of these regressors differs across the two wetland types.

As can be seen from Table 4 of the *online appendix*, all non-acre related saltwater interactions for both versions exhibit posterior inclusion probabilities that exceed the prior of 0.5, for some cases by a large margin. In comparison, inclusion probabilities for interaction terms range from 5 to 30 % in Moeltner (2019), where the SSVS approach produced more efficient benefit estimates. This raises strong doubt that these interactions are negligible and that the data can be pooled across the two wetland types along these dimensions. Furthermore, the posterior means for the interactions are of considerable numerical magnitude, and there is only limited ambiguity as to the direction of their marginal effect on wtp based on the $p > 0$ statistic, providing further evidence that pooling, or even partial information spillovers, are unlikely. This is not surprising given the substantial differences in most wetland and study characteristics across the coastal and freshwater groups.

The only interaction term with low inclusion probability for model M1c is the nonlinear deviation term for acreage, δ_γ, which was only chosen to be important 3.2% of the time across all iterations of the GS. While this result suggests that the marginal effect of acreage on wtp is similar across the two wetland regimes, any efficiency gains due to information-borrowing along this single dimension are unlikely to outbalance the efficiency losses introduced by the many significant interactions associated with the linear context-specific variables. A similar conclusion holds for the (small) deviation for the midpoint coefficient, $(q_1 + q_0)/2$, in model M3c.

On a final comparative note, the error variance σ^2, captured in the last row of the online table more than quadruples for the SSVS approach compared to the freshwater-only MRM for both model versions. This suggests that adding the saltwater data not only dilutes coefficient effects, but also introduces a substantial amount of error noise into the model. This conclusion is also supported by the larger posterior standard deviations for most context-specific coefficients compared to the corresponding freshwater only version.

Based on these results, we would not expect the SSVS model to produce measurable efficiency gains, if any, for BT predictions compared to the freshwater model. We therefore limit our BT example below to the freshwater-only case, but with continued comparison across our preferred models M1c and M3c.[9]

5. Benefit transfer example

To illustrate the application of our best-fitting MRMs (M1c and M3c) to BT, we simulate an increase in wetland acreage from a baseline of 10,000 acres (the sample median for the freshwater data) to a target level of 10,050 acres. This setting for q_0 corresponds reasonably well to realistic baseline wetland acreages for actual sub-watersheds, such as Hydrologic Unit Code (HUC) 0509 (Middle Ohio — 12,000 non-abutting wetland acres under baseline conditions), HUC 0510 (Kentucky-Licking — 3000 non-abutting acres), and HUC 1306 (Upper Pecos — 18,000 non-abutting acres). The target change of 50 acres per year, in turn, reflects preliminary estimates of potential annual losses in wetland areas from reduced mitigation requirements for non-jurisdictional wetlands for the typical affected hydrologic subregion (four-digit HUC). In some subregions, cumulative losses may reach several hundred acres over a period of 20 years. To verify that the predictions satisfy the adding-up condition, we implement this change in two increments, from 10,000 to 10,030, and from 10,030 to 10,050, in addition to the one-step scenario.

Settings for the remaining context-specific variables are chosen as follows: `lnyear` = 3.4 (log of (2018–1988), plus 1), `lninc` = 11 (sample mean), region = South-Atlantic/Gulf, and the only wetland service in addition to "supporting" is "cultural" (i.e. recreation). For comparison purposes, we generate predicted benefits for all four combinations of `local` and `forested`, given the documented importance of these variables in our meta-regression (see Table 4).

In terms of moderator variables, we set `lumpsum` to zero to allow our BT predictions to be interpreted as per-year values, which is typically reported in benefit cost analysis of resource management programs. In contrast, we average our predictions over both possible settings ("0" and "1") for indicator `volunt`, giving equal weight to each.

For all four `local/forest` scenarios, we report mean wtp, based on posterior predictive distributions that include error term effects in

[9] We also implement the BT example using the SSVS output for both specifications. Results are given in Table 5 of the online appendix. As expected, BT predictions flowing from the SSVS model show much larger posterior variability and exhibit unrealistically large posterior means and medians, especially for M1c. This directly reflects the inflated error variance of the SSVS model compared to its freshwater-only counterpart, as well as presence of "information-deficient" nuisance parameters in form of the interaction terms that had to be carried along during estimation.

Table 5
BT predictions (annual $s per household).

	M1c						M3c					
	Mean			Median			Mean			Median		
Scenario (acres, 1000s)	Low	Mean	High	Low	Mean	High	Low	Mean	High	Low	Mean	High
	Non-forested, Non-local						Non-forested, Non-local					
10 to 10.03	0.00	0.24	5.28	0.00	0.15	0.61	0.00	0.23	1.30	0.00	0.16	0.60
10.03 to 10.05	0.00	0.16	3.52	0.00	0.10	0.40	0.00	0.16	0.87	0.00	0.11	0.40
10 to 10.05	0.00	0.40	8.81	0.00	0.25	1.01	0.00	0.39	2.17	0.00	0.27	1.00
	Forested, Non-local						Forested, Non-local					
10 to 10.03	0.00	0.90	18.04	0.00	0.56	2.71	0.00	0.79	5.97	0.00	0.53	1.72
10.03 to 10.05	0.00	0.60	12.03	0.00	0.37	1.81	0.00	0.53	3.98	0.00	0.36	1.15
10 to 10.05	0.00	1.51	30.07	0.00	0.93	4.53	0.00	1.32	9.96	0.00	0.89	2.87
	Non-forested, Local						Non-forested, Local					
10 to 10.03	0.00	1.76	12.31	0.00	1.24	4.04	0.00	1.73	6.14	0.00	1.26	4.25
10.03 to 10.05	0.00	1.17	8.21	0.00	0.83	2.70	0.00	1.15	4.10	0.00	0.84	2.83
10 to 10.05	0.00	2.93	20.52	0.00	2.06	6.73	0.00	2.88	10.23	0.00	2.10	7.08
	Forested, Local						Forested, Local					
10 to 10.03	0.00	8.56	148.59	0.00	5.70	23.51	0.00	7.66	42.10	0.00	5.52	19.53
10.03 to 10.05	0.00	5.71	99.08	0.00	3.80	15.68	0.00	5.11	28.08	0.00	3.68	13.03
10 to 10.05	0.00	14.26	247.67	0.00	9.50	39.18	0.00	12.77	70.18	0.00	9.20	32.55

Mean = posterior mean.
Low (High) = lower (upper) bound of 95% highest posterior density interval.

the log-linear model before exponentiating to obtain actual dollar values, and median wtp, which sets error effects in the log-linear model to zero before taking exponents. For M3c, we add $\log(q_1 - q_0)$ to both sides of the predictive equation before exponentiating to obtain wtp for the full change in acres as opposed to average wtp per acre. As mentioned above, all wtp estimates are best interpreted as annual benefits per household.

Table 5 presents results of our example BT application for both M1c and M3c. For each version, the table shows the posterior mean of the predictive construct (mean or median), as well as the lower and upper bound of the corresponding highest posterior density interval.[10]

While not explicitly captured in the table, adding up errors are zero to the third decimal for all scenarios and both model specifications. While this is as expected for M1c due to its structurally built-in AU compliance, it is noteworthy for M3c. As shown in Moeltner (2019), AU compliance for M3-type models hinges largely on the magnitude of the estimated quality parameter for the midpoint variable, given as γ in Eq. (6) above. The closer γ is to zero, the more likely AU will hold. As can be seen from Table 4, the estimated posterior mean for γ is indeed small (0.009), with an equally small posterior standard deviation (0.007). Apparently, for our data this is small enough to virtually eliminate AU errors.

As can also be seen from Table 5, BT predictions are also very similar between the two models, for both the " mean" and "median" implementation of the predictive algorithm. As expected, given our original estimation results for the freshwater model, forested and/or local wetlands are valued considerably higher than non-forested and/or non-local types, by a factor of close to four for forested, and a factor of over seven for local, for both mean and median wtp compared to the non-forested, non-local scenario. At the upper end, the addition of 50 acres of local, forested wetland generates expected mean benefits per household and year of $13– $15, or $0.26– $0.29/acre, as can be seen from the last row of the table. In contrast, 50 added acres of non-forested wetland that is not in near proximity of the target population are valued, on average, at a more modest $0.4, or approximately $0.01/acre, per household and year.[11]

While HPDI bounds are comparable across the two models for the "median" estimates, they are two to three times tighter for M3c compared to M1c for the "mean" estimates. Evidently, M1c, with its non-linear component, tends to generate more extreme wtp values during the exponentiation process than the fully linear M3c. To the extent that mean estimates (with incorporated error effects) are required, and upper HPDI bounds are informative for policy decisions, this would favor M3c over M1c for the application at hand. However, as for model fit based on BFs, compliance with AU for linear models such as M3c has to be assessed on a case-by-case basis across different empirical contexts.[12]

[10] As described inter alia in Koop (2003), the α-% HPDI is the smallest interval over the range of a given distribution that includes α % of the density mass. It is a common Bayesian statistic used to describe the spread of a given distribution, and/or confidence bounds for a given parameter of predictive construct of interest.

[11] As pointed out by a reviewer for the nonlinear model M1c, for small changes in q, such as considered in this application, the corresponding segment of the underlying wtp function will be approximately linear, especially given the small values for the acreage/curvature parameter γ (0.008). This translates into approximately linear estimates per acre along the entire policy range. This pseudo-linearity per-acre does not hold for larger changes, as is evident from Moeltner's (2019) large-step example in a water quality context. As can be seen from Table 5, approximate linearity per-acre can also be observed for M3c, for analogous reasons.

[12] At the suggestion of a reviewer, we also performed a leave-one-out cross-validation convergence validity test (LCV test) to further assess the relative out-of-sample predictive ability of our two preferred specifications. Details are given in the online appendix. Results are again almost identical across both models, with average absolute percentage errors (APEs) based on mean predictions (allowing for error noise) of approximately 120%, and average APEs based on median predictions (ignoring error noise) of 76–77 %. These LCV results for median predictions (which most closely reflect standard practice in the literature) are generally in line with the existing meta-literature. For example, Vedogbeton and Johnston (2019) report a mean APE of 72% for their coastal wetland application. Similarly, Brander et al. (2007) find a mean APE of 74% for their wetland meta-analysis. Mean APE figures of 65–80 % also seem to be the norm in non-wetland meta-applications, such as Johnston et al. (2017) and Johnston et al. (2019). This consistency with existing contributions is

On a final note, we would like to reiterate that due to the AU property – structurally satisfied for M1c, and empirically satisfied for M3c – the total change in acreage, here 50, could in theory be achieved with any desired number of (potentially annual) incremental steps without changing the total wtp estimate (e.g., 2.5 acres per year over 20 years). Furthermore, at every point along the way, the model will produce correct estimates of the benefits that have already been created (or lost), and the benefits that are still "on the table" (or at risk). As stated at the onset, this is a an important feature of these models, as real policy changes in wetland areas at any given location (e.g., wetland losses from reduced mitigation requirements due to definitional changes of WOTUS) will likely occur incrementally over prolonged time horizons.

6. Conclusion

With this study, we respond to the ongoing debate on the legal protection of wetlands, and the concurrent need to understand the societal benefits created by them, by illustrating how a recently introduced MRM framework that is consistent with economic theory can be adapted to generate BT predictions for incremental changes in wetland acreage in a given spatial location over a long time horizon.

Compiling a new meta-data set of wetland valuation that includes studies as current as 2016, and following best practices in study selection and data preparation as recommended by Stanley et al. (2013), we show how Bayesian model comparison tools can be used to identify promising statistical models for parameter estimation and, subsequently, BT application. From an econometric perspective, this adds over Moeltner (2019) who uses only the equivalent to our models M1a, M2a, and M3a, that is specifications with a relatively complex error structure. For our sparser data set, it turns out that more parsimonious specifications that abstract from within-study random effects and error heteroskedasticity perform best (e.g. M1c, M3c).

Starting from these models, we then employ the SSVS algorithm proposed in Moeltner (2019) to examine if and to what extent the coastal/salt marsh portion of our meta-data should be allowed to influence BT results for a freshwater context. We find that for this data set and in contrast to Moeltner's (2019) water quality application, using only the context-specific portion of the data (here: freshwater wetlands) produces the most efficient BT predictions.

We then illustrate how this econometric framework could be used to derive BT predictions for actual watersheds. As noted above, careful consideration is needed in selecting BT transfer setting for acreage due to the convexity of the wtp function for both of our preferred models (M1c, M3c) implied by the estimates for the corresponding curvature parameter. To avoid unreasonably inflated predictions, as would result from using baseline acreage for a large region or an entire state, we use stylized, sample-informed settings for acreage. Conveniently, these figures are comparable to wetland coverage in real-world sub-watersheds (e.g., HUC4 or HUC8). We find that a forested, local version of our wetland scenario generates by far the highest benefits, stressing the importance of controlling for these two important context-specific variables.

To benefit transfer practitioners, we thus recommend (i) estimating wtp on a watershed by watershed basis or use sample-informed settings for baseline and policy acres to ensure acreage magnitudes lie within the meta-data range, and (ii) allowing for distinct predictions along the forested/non-forested and local/non-local dimensions.

From a modeling perspective, we not only confirm the "tolerable" AU properties of M3-type linear models reported in Moeltner (2019), but in fact find that for our application the linear model M3c satisfies AU to any policy-relevant precision. It also outperforms the nonlinear M1c based on predictive efficiency, at least for BT scenarios that fully incorporate error noise. This may not always be the case for a given BT context and meta-data, but at least suggests leaving the door open for linear models that may not satisfy AU by construction, but may do so "ex post", that is empirically, given parameter estimates for the quality variable under consideration.

Ultimately, it is our hope that these new meta-data and refined econometric tools will be helpful in informing the current discussion on the economic importance of different kinds of wetlands, and how they should be incorporated into the Clean Water Act.

(*footnote continued*)
encouraging, especially considering that our sample size is substantially lower than that of all of these other studies.

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