Decision support modeling for multi-attribute water quality in the Narragansett Bay watershed

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Abstract

We develop an integrated assessment model for spatially simulating water quality changes and social welfare effects for recreational use and non-use as a function of common point and non-point source pollution management interventions. This extends prior modeling by incorporating a broader suite of water quality characteristics beyond phosphorus and nitrogen that are known to affect water quality. Beyond demonstrating the feasibility of such a model, we show the implications of omitting water quality factors on model estimates and find that in some cases a smaller set of water quality attributes may not significantly impact estimates of willingness to pay. We derive these lessons in a case study of Narragansett Bay, a coastal estuary that has recently experienced significant changes in nutrient loading due to a combination of point and non-point source changes and find that recent wastewater treatment upgrades are providing millions in annual value to adjacent residents.

Paper

Introduction

Narragansett Bay is a large estuary in the U.S. Northeast that supports the well-being of more than 2 million adjacent residents through valued uses such as tourism and recreation, commercial and recreational fishing, and more (Figure 1). Since 2000, management of point source pollution in the watershed coupled with land use change have significantly changed the quality of water flowing into the Bay (Table 1). Wastewater treatment upgrades, in particular combined sewer overflow abatement investments, have decreased nitrogen and phosphorus loading into the bay by 55 percent and 45 percent respectively (NBEP, 2017). Simultaneously, land use patterns have changed over this same span: by area, in 2001 the watershed was 33% urbanized, 57% forested, and 6% was devoted to agriculture, by 2011 these figures were 36%, 55%, and 5% respectively. Limited monitoring throughout the bay has complicated establishing a net effect of how these changes have manifested in water quality attributes or proxies in the bay, such as water clarity, dissolved oxygen, chlorophyll *a*, and beach closures (NBEP, 2017; Oczkowski et al., 2018), though some evidence suggests decreases in the bay for levels of total nitrogen (TN), total phosphorus (TP), and chlorophyll *a* as well as an increase in water clarity (Oviatt et al., 2017).

Given the limited information in the watershed about the effect of recent significant changes of key drivers in water quality, there is a strong desire from stakeholders and decision makers for a better understanding of the effect of these changes on water quality and human well-being. This need for decision-relevant information on water quality and its effect on well-being is not just a regional consideration; measuring the effect of a given intervention on downstream water quality is complex (Keeler et al., 2012), modeling frameworks often are poorly integrated between economics and natural sciences and stop short of measuring change in well-being (Brauman, 2015; Polasky et al., 2019), and even those studies that do link water quality interventions to changes in well-being tend to undercount many types of benefits (Keiser et al., 2018). With nearly two trillion dollars spent on reducing pollution in surface waters in the U.S. since 1960, there is still considerable uncertainty over the net social welfare implications of water quality improvements from large scale policies like the Clean Water Act and the Conservation Reserve Program (Keiser et al., 2018). While this can partly be attributed to limited spatial and temporal monitoring, and potentially even measurement error in existing U.S. national datasets (Keiser, 2018), there is simultaneously a need for improved integrated assessment models (IAM), especially of the sort that can produce marginal social welfare estimates from common interventions smaller than national programs like the Clean Water Act (Keiser & Muller, 2017).

This study develops a spatially-explicit IAM that evaluates willingness-to-pay (WTP) for changes in six dimensions of estuarine water quality that link back to point and non-point source pollution in the upstream watershed. We use the model to evaluate retrospective and prospective changes in welfare from heuristic and stakeholder-driven policy scenarios. The IAM estimates WTP using a benefit transfer function derived from a meta-analysis regression of stated preference surveys that measure the value of recreational and non-use values as a function of water quality (Johnston et al., 2005; Johnston et al., 2017). The function employs a water quality index (WQI) as a predictor of WTP that integrates multiple key attributes of water quality into a single measure on a 0 - 100 scale (Vaughan, 1981; EPA, 2009). Each water quality attribute is modeled spatially by characterizing its physical transport and fate as a function of watershed characteristics and information about non-point and point source factors, including wastewater treatment facilities (WWTF), onsite water treatment systems, and more than 350 dams. The IAM structure follows the form of an ecosystem service assessment (Freeman III et al., 2014; Olander et al., 2018), using geospatial data and process-based and empirical modeling to provide decision-relevant outputs at each step of the model (Figure 2).

The water quality and benefit functions employed in this IAM have facilitated a wide array of policy analyses (e.g. (EPA, 2009; EPA, 2010; Meehan et al., 2013; EPA, 2015; Johnson et al., 2016); however, prior modeling efforts employing these functions have tended to feature only one or two water quality factors, usually nitrogen and phosphorus, with limited capacity to simulate spatial and aspatial policy impacts even with a limited set of factors. Beyond the use of these particular functions, it is common in the context of IAMs for water quality to be represented by a pared down set of water quality factors; this typically is due to the scope of the study being narrowly defined to a subset of effects/uses for which the extra effort to expand the suite of pollutants would be unnecessary. Examples include IAMs that study the use of cost-effective conservation to reduce nitrogen and phosphorus as the primary drivers of hypoxia in the Mississippi Basin (Rabotyagov et al., 2014) and sediment impacting coral reef health (Oleson et al., 2017).

We expand prior modeling efforts employing these water quality and WTP functions with a more comprehensive suite of physical models driving six key water quality variables: total nitrogen, total phosphorus, total suspended sediment, dissolved oxygen, chlorophyll A, and bacterial contamination. As several of these water characteristics are not generally known to be correlated with each other and all of them are thought be drivers of water quality that impact use patterns (Vaughan, 1981; Cude, 2001), omission of any of these factors in an IAM could potentially bias water quality estimates. Thus, a main contribution of this study is to investigate the feasibility of including these additional factors into an IAM for water quality and characterizing the potential for bias if water quality characteristics are omitted. We do so in the context of our case study in Narragansett Bay, with additional research questions motivated by outreach and consultation with stakeholder groups throughout the watershed following best practices for integrating science in decision making (Ruckelshaus et al., 2015; Posner et al., 2016). Through this interaction, several questions emerged as key considerations for decision-making that we explore here:

- What was the change in overall water quality flowing into the bay from 2001 to 2011? How has this changed with respect to point and non-point source pollution? How has recreational use value and non-use value of Narragansett Bay changed due to changes in water quality, and how has this differed for point versus non-point source pollution? How has this changed spatially across the Narragansett Bay watershed and across different water quality contaminants?
- Under current conditions, what are forests' contribution to changes in well-being from water quality improvements in the bay? Where are priority areas to conserve?
- How do dams influence downstream water quality?

In the study area of Narragansett Bay, a key finding is a willingness to pay of $51 and $38 million per year for recent point source infrastructure upgrades in the upper and lower bay respectively. Before we answer the remainder of these questions, we turn to the details of the modeling.

Methods

Water quality enhancements can result in a wide array of benefits that are mediated by environmental factors and the location and use preferences of affected populations (Keeler et al., 2012). The breadth of the services impacted and the requisite modeling and data collection effort to estimate welfare effects from changes in these services has increasingly led researchers to focus on providing generalizable and scalable tools for decision support, with a particular focus on the use of benefit transfer to facilitate analysis (Plummer, 2009; Johnston & Thomassin, 2010). This approach to valuation uses estimates of WTP for water quality improvements that have been derived elsewhere and applies them at a new study site. It has been tested widely in the context of water quality and evidence generally supports the use of benefit transfer function approaches when there is no readily comparable site to borrow values from and limited capacity to originate a stated preference survey (Rosenberger & Loomis, 2000; Bateman et al., 2011).

The benefit transfer function applied in our IAM, described in detail in (Johnston et al., 2005) and (Johnston et al., 2017), was developed with that purpose in mind, facilitating water quality assessments through a willingness to pay function synthesized from 51 stated preference studies for water quality in the U.S. Derived using a meta-regression analysis, the function estimates willingness to pay as a function of baseline and changes in water quality for recreational users (swimming, fishing, boating) and non-users, while also capturing variation in site-specific geophysical and demographic attributes (Figure 3). The function is estimated as translog, where the dependent variable (WTP), water quality (baseline and change), and other continuous independent variables are transformed with natural logs to fit non-linear relationships in the data and ensure that willingness to pay approaches zero as these variables approach zero (Figure A.1).

Producing estimates of WTP from this function requires several steps to ensure consistency with the assumptions of the underlying primary studies. While the appendix expands on this modeling, several of these steps are worth emphasizing for their implications for the broader IAM. In particular, the primary stated preference studies this function is based on solicit WTP for changes in water quality typically at an annual time scale; consequently, consistent temporal water quality resolution should match this. Spatially, the stated preference surveys asked about discrete water bodies, though an estuary as large as Narragansett Bay has different oceanographic and use characteristics across its range and may be best represented by multiple zones. Similarly, geographic boundaries for impacted populations were *a priori* imposed in the source WTP studies, leaving the researcher using this WTP function to make a judgment call about the affected market area. Based on consultation with local stakeholder and experts in the watershed, we broke the study area into two zones based on the different oceanographic conditions and used the 848,735 households in the Narragansett Bay watershed boundary as the affected market area. The IAM resolves pollutant movement at scales smaller than the zone level and therefore could be reapplied for any values of market area and spatial zoning of the focal resource. For this study, all water quality calculations and WTP values are calculated based on the overall WQI change induced by an intervention in the respective watershed that corresponds to each of the two zones.

The benefit transfer function uses a water quality ladder to relate multidimensional water quality to WTP. There are more than 50 different water quality indices/indicators developed to track water quality (Plummer et al., 2012); here we select an approach based on the Oregon Water Quality Index (Dunnette, 1979; Cude, 2001) developed by the United States Environmental Protection Agency (EPA, 2009). Variants of this index have been widely used to aggregate disparate water quality characteristics into a single index value that can be translated to a public audience qualitatively, typically by demarking thresholds of increasing water quality by use types: safe for boating, fishing, swimming, and drinking (Vaughan, 1981; Carson & Mitchell, 1993; Houtven et al., 2007; EPA, 2009). The EPA WQI ranges from 0 – 100, where a value of 25 indicates safe for boating, 45-50 indicates safe for fishing, and 70 indicates safe for swimming. Narragansett Bay is a large estuarine system with distinct biogeochemical properties from freshwater systems; consequently, the WQI index we use was modified by the EPA to include relevant marine water quality indicators including dissolved oxygen, fecal coliform, chlorophyll *a*, TN, TP, and total suspended solids. We substitute enterococcus for fecal coliform coliform concentrations based on updated federal guidance for using enterococcus as the water quality standard for recreational waters.

Translating raw contaminant concentrations to a total WQI value for use in the benefit transfer function and the broader IAM involves several steps. As our IAM is designed for spatial scenario prediction and to have the capacity to trace the marginal damage/benefit to water quality users and non-users back to spatial interventions such as land use change, we cannot rely completely on observed data and must employ some form of modeling for scenario analysis. Even estimating baseline contaminant concentrations across the watershed requires some modeling as there is insufficient monitoring coverage for all of the six of the contaminants in the WQI. Therefore, a first step towards calculating a WQI is obtaining data on each of the six contaminants in the watershed, with an eye for limitations in these data that can inform appropriate modeling approaches. The approach taken to spatially model each subcontaminant is described in detail below; however, we continue here with the WQI to provide context for modeling choices. The second main step is, with appropriate concentration data for all six variables in hand, converting these data to subindex values for each contaminant expressed on a 0 – 100 scale. The subindex transformation curves used here are given in the appendix (Table A.1) and are sourced from (EPA, 2009). Finally, these subindices are combined to arrive at the final WQI value by using a weighted geometric mean function, shown in Figure 3.[i] Values for the raw concentrations, subindex values, and overall WQI value are calculated by zone in Narragansett Bay for all scenarios and these overall WQI values are inputs to the WTP benefit transfer function.

This IAM extends prior efforts by spatially modeling a suite of six water quality characteristics; however it is worthwhile to reflect on the nature of this particular WQI function and whether this additional effort is warranted by exploring how the WQI varies if only a subset of characteristics is considered. In applications using only TN as a water quality factor, if TN was at maximum quality (100) but all other unobserved characteristics are at minimum quality (10), the resulting WQI calculation of 100 would miss that the unobserved factors would reduce this to a value of 14 out of 100. Even in a more favorable setup, where we assume the researcher includes TN and TP and accounts for the relationship these have on dissolved oxygen and chlorophyll *a* concentrations (as estimated below), setting the known variables at max quality and the unknown variables (enterococcus and total suspended solids) at minimum quality results in a WQI of 44 versus 100. This simple exercise demonstrates that there is significant scope for differences in overall water quality by omitting pollutants and the importance of including these where practical.

For modeling subcontaminants that link point and non-point source interventions to water quality, we evaluated a wide array of approaches that range on the continuum of mostly process-based to mostly statistical in nature. Process-based hydrological models have the appeal of more ready interpretation, lend themselves readily to spatial analysis, and are suited for analysis beyond observed historical data ranges that make them particularly suitable for scenario analysis (Nearing et al., 1989); however the maturity of research on the six contaminants differs widely and for several of these contaminants there is limited theoretical understanding about the downstream effects of typical management interventions. Moreover, model selection in hydrology has been found to be largely driven by legacy and regional model preferences versus methodological considerations (Addor & Melsen, 2019). For the case of an IAM that employs a wide array of models for subcontaminants with an eye towards applied decision-making, we prioritized on process-based models and ease of use subject to data availability and consistency with the assumptions and form of the water quality index and the benefit transfer function. These considerations resulted in modeling TN, TP, and sediment using the process-oriented InVEST ecosystem services modeling platform and using reduced form empirical models for enterococcus, chlorophyll *a*, and dissolved oxygen.

Nitrogen and phosphorus transport modeling for non-point source pollution was done using the InVEST nutrient delivery ratio model (NDR) (Hamel et al., 2017; Redhead et al., 2018). This model uses a mass-balance approach to hydrologically route diffuse sources of nutrients, estimating long-term steady-state surface and subsurface nutrient flow to streams. Nutrient sources and retention rates for different land categories are combined with a topographic routing model and a nutrient transport index to estimate the net landscape contribution of nutrients at the watershed outlet. Similarly, the InVEST sediment delivery ratio model was used to produce estimates of sediment transport to catchment outlets on Narragansett Bay (Hamel et al., 2015). Similar to the NDR model, the SDR model calculates net soil loss using land characteristics related to land use and other forcing factors via the revised universal soil loss equation (Renard et al., 1997), as well as a sediment transport index that moves sediment through space based on the hydrological connectivity of the watershed. Both of these models are best considered as producing relative values without calibration due to the index-based approaches used to transport contaminants through space.

The process for parameterizing and calibrating these models is described in the appendix; however, we note several important points here. SDR and NDR produce annual estimates of sediment, TN, and TP load at the catchment outlet; no in-stream processes are included in the model. Both models produce maps that demonstrate net export at the resolution of the land cover map used in the analysis. As a result, net export can be traced back to particular locations within the watershed, can be aggregated at different potential intervention scales, and land cover maps featuring different non-point source interventions can be compared to estimate spatial differences in export.

Several additional steps are necessary to estimate sediment and nutrient concentrations; the final step, calibration, we cover in the appendix, but here we briefly discuss dams, point source loading of nutrients, and water flow. There are 352 dams in the watershed that have been shown to act as point sinks for nitrogen (Seitzinger et al., 2002; Gold et al., 2016) and sediment (Meade, 1982; Renwick et al., 2005). We modeled the retention effect for nitrogen using estimated retention factors (% of TN load retained annually) derived for all known dams in the watershed (Gold et al., 2016). As many reaches feature multiple dams, we estimated the cumulative spatial retention factor using a directed graph algorithm and a spatially delineated set of upstream watersheds for all dams to appropriately accumulate retention while moving down the watershed and apply the cumulative retention effect to the correct set of subwatersheds. An analytically identical approach was taken to estimate sediment retention by reservoirs across space, where the retention factor for each dam was calculated using a Brune curve (Brune, 1953). These retention maps were then multiplied by the export maps to create net export maps of TN and sediment and total annual non-point loads for each zone in the bay. The literature is less developed on the role of dams in retaining phosphorus, so it was left out of the modeling.[ii]

Point source TN and TP loading from WWTFs into each zone in Narragansett Bay was gathered from a recent nutrient budget analysis in the bay (NBEP, 2017). WWTFs were grouped by zone and total load values were calculated by summing for each zone and for the relevant analysis years, 2001 and 2011.

The load-based outputs of the NDR and SDR models and the point source loading require information about flow to construct concentration estimates. There is monitoring of river flow into Narragansett Bay from several main tributaries (NBEP, 2017), however a significant area is ungauged and needs to be estimated to provide full coverage for all tributaries in the watershed. To estimate annual flow volumes for both watershed zones in Narragansett Bay, we used estimates of mean annual runoff volume per land area in the Narragansett Bay watershed (Ries, 1990), producing estimates of total flow by zone per year using the respective zone sizes. Summing point source loading with net non-point source loading after dam retention, we calculate mean annual concentrations for these three contaminants by dividing their respective total loads by the flow for each zone. These concentrations are representative of the mean annual concentrations of these contaminants entering into each zone from upland and are the values we use in the IAM to calculate water quality in each zone. In this model, this freshwater is not explicitly mixed into Narragansett Bay using an oceanographic model and as such becomes less representative of bay water quality further from shore.[iii]

The other three subcontaminants were modeled using local data and regression models informed by the supporting peer-reviewed literature for each and are explained in detail in the appendix. The main goal was to use these models in a predictive way in the IAM, linking point and non-point source interventions to changes in the concentration of these contaminants where supported by theory and data, versus leaving these out of the WQI or holding them at baseline levels for all scenarios. In specifying the model there was a practical balance to be made between fit and data availability, where data availability is a two-fold issue: first, was there enough data within sample to include the desired predictors; and second, was there enough data out-of-sample to extrapolate the regression results to the broader study area? While we were able to estimate more comprehensive models that included other potentially relevant predictors such as water temperature, salinity, pH, and other commonly sampled water attributes, there is limited coverage of these variables in the bay and not enough data to support the estimation of mean annual values for each zone. Because of these data limitations, we limited the predictors to TN and TP and an interaction term of these to estimate dissolved oxygen and chlorophyll *a* concentrations. It is clear from the range of model specifications that this comes at the cost of model fit. Moreover, this creates a dependency between the models for TN/TP and dissolved oxygen and chlorophyll *a* where errors in the TN/TP models will propagate through these other contaminant estimates. However, constructing the model in this way allows us to estimate the induced effect of interventions that we otherwise would have a difficult time linking in a direct way back to changes in point and non-point source management.

Dissolved oxygen and chlorophyll *a* concentrations have been found in a wide array of studies to be correlated in estuaries with nitrogen and phosphorus concentrations (Ryther & Dunstan, 1971; Hoyer et al., 2002; Prasad et al., 2011; Bbalali, 2013; Rai & Rajashekhar, 2014), so we used these as the independent variables in the regression specifications for both contaminants. Enterococcus concentrations were estimated using a regression approach linking key drivers observed in the literature to levels observed in Narragansett Bay with a longitudinal dataset from the Rhode Island Department of Health. The peer-reviewed literature investigating the effect of various human uses and watershed characteristics on pathogenic bacterial contamination has little in the way of theoretical modeling and is dominated by statistical studies with varying conclusions about the effect of drivers like land use, population density, onsite water treatment system (septic system) density, wastewater treatment network coverage, livestock density, rainfall, and more (Fisher et al., 2000; Frenzel & Couvillion, 2002; Tong & Chen, 2002; Walters et al., 2011; Sowah et al., 2014; Vitro et al., 2017; Sowah et al., 2017). We estimated a variety of models using combinations of many of these factors, settling on one with predictors for urban/forest/agricultural land use (% of the watershed by area), prior 7 day rainfall (inches), wastewater network coverage (% of watershed by area), and onsite water treatment system density (#/km^2). We only modeled this relationship for coastal subwatersheds (HUC 12 level) directly adjacent to the bay, both in the estimation and prediction step, following approaches in the literature and under the assumption that this would provide the best chance to observe significant effects given the weak prior results in other studies.

Results

Observations in the watershed alone do not provide enough coverage to estimate water quality using the WQI for the years 2001 and 2011, so we first present the results of our water quality estimation for both zones using the IAM (Table 2). Water quality conditions in 2001 and 2011 are given as an attribute-specific water quality index values for each attribute and raw concentration values (in parentheses) for each of the six attributes. In 2001, sediment, dissolved oxygen, and enterococcus levels were low enough to result in relatively higher water quality subindex values than the other three contaminants across both zones, with sediment being more of an issue in zone 2 and dissolved oxygen more of an issue in zone 1. Nitrogen and phosphorus concentrations were high enough to drive poor subindex values for those contaminants as well as induce low water quality with respect to chlorophyll *a*, with zone 1 being worse on all values versus zone 2. Overall, water quality in zones 1 was 57 and in zone 2 was 65, values that fall between a water quality level adequate for fishing and for swimming.

Nearly all subindex values increased between 2001 and 2011 due to lower loads and concentrations, with decreases in TN and TP loading pushing the overall water quality for both zones above the level considered adequate for swimming (EPA, 2009). Net loads for TN and TP decreased markedly due to wastewater treatment facility upgrades over the time period (Table A.2), despite slightly higher estimated loads from non-point sources of roughly 1% for both zones and contaminants. Sediment load increased by 11% in zone 1 and 3% in zone 2: this trend did not push zone 1 below the threshold for maximum water quality for the sediment subindex (28 mg/L), but did reduce the sediment subindex in zone 2. Enterococcus concentrations also increased in both zones in 2011, though this had a negligible effect on the subindex water quality value as it had previously been well below the threshold for the maximum possible value (50 cfu/100mL).[iv] Greater enterococcus concentrations were driven by increased urban land cover in bay-adjacent HUC12 watersheds in 2011 as compared to 2001.[v] Chlorophyll *a* concentrations reduced in zone 1 but increased slightly in zone 2 due to an increase in phosphorus loading from both point and non-point sources. Changes in nutrient reduction tend to change primary production only slightly in eutrophic systems (Oviatt et al., 2017), so the small magnitude of change here despite the large change in nutrient loading is not unexpected. This overall water quality change between 2001 and 2011 translates to an annual household willingness to pay estimate of $59.6 for zone 1 and $44.8 for zone 2, or $50.6 million and $38 million respectively for the 848,735 households in the Narragansett Bay watershed (Table 3).

We also look at the net retention effect dams play in ongoing sediment and nitrogen retention by conducting a heuristic exercise of removing all dams and comparing that to the existing water quality index in 2011 in both zones. We find that dam removal in the watersheds of zone 1 and zone 2 would reduce water quality by 6.3 and 2.5 points in their respective zones in the bay. A longstanding observed empirical differential between willingness to pay for a water quality gain and willingness to accept payment for an equal water quality loss (Kling et al., 2012) suggests that the negative willingness to pay estimates here are no better than a first-order estimate of potential lost social welfare and highlight a shortcoming of the willingness to pay function used in the IAM in that it cannot be used to estimate willingness to accept.

As a contribution of this work is to explore the implications of using this water quality index and benefit transfer function with contaminants beyond nitrogen and/or phosphorus, we present the results of our retrospective analysis from 2001 – 2011 using two alternative formulations of the water quality index. The first WQI function only includes TN and TP and reweights the WQI correspondingly to simulate a study that only went as far as to include these contaminants. The second WQI function is a reweighted function that adds dissolved oxygen and chlorophyll *a*. These have been shown to be significantly correlated with nitrogen and phosphorus in estuarine systems, and since they are generally expected to move together, we would expect this function to approximate the results of the function that only includes nitrogen and phosphorus. Comparing across all three specifications of the WQI, the two alternate specifications that remove some contaminants have a generally lower overall water quality value, however the WQI change values are not far off from the full index and the willingness to pay estimates are also reasonably close. Lower overall water quality is due to the omission of enterococcus and sediment, which are both near their maximum values in zone 1 for both time periods and above the modeled total WQI for the alternate specifications in zone 2 for both time periods. However, change values are similar as the main dimensions of change in this watershed from 2001 to 2011 are point source changes in TN and TP and not the omitted sediment and enterococcus attributes. Moreover, because the benefit transfer function is not particularly sensitive to changes in the baseline water quality and quickly flattens as a function of water quality change (Figure A.1.) we observed qualitatively similar implications for willingness to pay using the three different specifications.

Finally, we addressed the question of where to prioritize conservation in the watershed by estimating the change in the water quality index (for the appropriate tributary zone) when converting all natural area in a (HUC 12) subwatershed to development and attributing the value of that change back to the natural areas in that subwatershed.[vi] We visualize this using a marginal values map (Ricketts & Lonsdorf, 2013), where each subwatershed's value is the marginal contribution of that particular watershed, with all other watersheds held at baseline values (Figure 4). This provides an estimate of the non-point source pollution retention value of natural ecosystems in a watershed relative to an alternative of developed land, and by holding all else constant we avoid complexities associated with the strong landscape interdependency of hydrological routing (Guswa et al., 2014).

Changes were modest, with a maximum change between -.99 and .43 points on the 0-100 water quality scale. This reflects several different important factors: 1) A significant portion of land adjacent to the bay is already urbanized, with lower potential water quality impact from conversion of natural lands to developed lands, all else equal; 2) Dams play a significant role in retaining nitrogen and sediment in-stream leading to lower influence of upstream export/retention by natural lands, all else equal; 3) Transitioning to development from natural areas reduces sediment transport to the bay by trapping sediments, a process that largely accounts for the increased water quality observed in subwatersheds flowing into zone 2 (where sediment levels are responsible for low baseline water quality; 4) These results implicitly capture existing pollution regulations for developed areas that may mitigate pollution that would occur in the absence of these laws; 5) Several of the subcontaminant concentrations are below their respective thresholds necessary for a maximum subindex quality score in the 2011 baseline, therefore increases in these contaminants from development would only change the score if the increase is large enough to push the contaminant level past the threshold. We do not monetize these changes as they are small enough to raise concerns that they would not be noticeable and inconsistent with the scale of water quality change that respondents were asked about in the WTP benefit transfer function metadata.

Discussion

Here we report on an IAM that can characterize water quality in a focal resource with incomplete spatial information on contaminants, as well as spatially simulate the effects of common point and non-point source interventions on water quality. These effects are reported as changes in raw contaminant levels for a suite of six key drivers of water quality, as well as qualitatively on their own and integrated together using subindices and an aggregate water quality index. The IAM links these water quality metrics to a benefit transfer function to allow for the estimation of recreational use and non-use willingness to pay values that arise from changes in water quality. We apply this IAM in the context of a watershed experiencing dynamic point and non-point source changes in pollution over recent years to estimate the change in social welfare attributable to the effect these changes have had on the regionally important downstream resource, Narragansett Bay. This analysis demonstrates that significant regional value has been created mainly as a function of improvements to wastewater treatment facilities since 2000.

Several other points with broader implications stand out from the application in Narragansett Bay. We took advantage of the IAMs flexibility to investigate an often overlooked, but increasingly important (Gold et al., 2016), part of addressing a significant legacy of small-scale dams in the United States. Dams provide an ongoing retention effect over several key drivers of decreased downstream water quality, and while individually this effect of a dam removal is relatively small in our study area, the cumulative effect would be large enough to significantly offset the gains realized from wastewater treatment upgrades in both zones of Narragansett Bay. As part of a comprehensive watershed management plan, this additional information can be useful when investigating tradeoffs against other potential benefits of dam removal (Roy et al., 2018).

We also investigate the role that existing forests play, relative to an alternative development use, in maintaining water quality in Narragansett Bay by conducting a marginal mapping analysis by subwatersheds where all natural areas are replaced by development. While forests and wetlands play a retention role in the transport of nutrients and sediment into adjacent streams (Allan, 2004), here we are more accurately measuring the net effect of an alternate development use that also includes unique export and retention factors of developed areas (for example, impervious surface tends to trap sediments) mediated by the effect of dams. We find modest marginal water quality index impacts from this transition across the watershed: in some areas this is due to an existing high proportion of urban land, in others it is due to cumulative dam retention, and overall this land features very little agriculture and fertilization relative to other commonly impaired watersheds with severe downstream impacts, such as the Mississippi River basin (Rabotyagov et al., 2014). While it may be tempting to assume that conservation would have limited impact in these watersheds, it is important to note that there is likely a greater cumulative effect at larger scales than the HUC 12 subwatershed level, though such large scale interventions are typically beyond the scope of even process-based models.[vii] We did not evaluate localized water quality effects on freshwater resources that are also extremely valuable in this watershed, such as the Scituate Reservoir that supplies drinking water to over 60 percent of the residents of Rhode Island. We also did not evaluate willingness to pay for drinking water or any of the other ecosystem services provided by forests. While most of these are beyond the scope of the IAM, modeling freshwater water quality for recreational and non-use purposes is an obvious potential extension.

There are a broad array of potential water quality indices that could be substituted into the IAM; we selected this water quality ladder as it has been used previously in the U.S. for rulemaking by the Environmental Protection Agency and has a degree of scientific support having been developed through expert elicitation and subject to review for consistency (Walsh & Wheeler, 2012; Swamee & Tyagi, 2000). Here we extend prior evaluation of this index by evaluating the willingness to pay implications of omitting water quality attributes, finding that there is the potential for wide discrepancy based on what is omitted from the index in the applied setting of a real estuarine system. However, this discrepancy does not appear to significantly affect our estimates of water quality change or willingness to pay. This property is wholly due to the fact that the main water quality changes in our case study were to subindices that were not at their max or min thresholds – a property that may not extend generally. The functional form of the chosen benefit transfer function quickly plateaus as a function of WQI change and is relatively insensitive to a shift in baseline water quality, so as long as WQI change estimates are expected to be similar when omitting contaminants from the WQI, then willingness to pay estimates may be close enough when weighed against the sizable effort required to model all six contaminants.

There are a wide array of limitations and avenues for improvement for this IAM, most of which are common to the current state of hydrological or benefit transfer modeling.[viii] The foremost issue unique to this work is that large integrated models increase the number of potential sources of uncertainty, something we explore here in a very limited way in the modeling for each pollutant and do not attempt to compound throughout the model. The addition of four pollutants to the set typically used to model water quality scenarios relied on fairly limited or conflicting peer-reviewed evidence linking these additional pollutants either directly or indirectly to common management interventions. This was particularly the case with the enterococcus modeling, where prior studies had found a range of conflicting evidence that land use plays a role in observed concentrations, suggesting this might be highly context specific or the underlying processes are not well understood theoretically. This underscores the broader model uncertainty across all subcontaminants due to the lack of unifying theoretical models in hydrology (<clark_2016>; <mizukami_2017>). While model uncertainty will be a longer term issue in the respective subfields that comprise this IAM, a clearer understanding of parameter uncertainty is an obvious next step for this model to increase confidence in our results,[ix] especially at scales smaller than the entire watershed where WQI values are small in magnitude.

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Figures

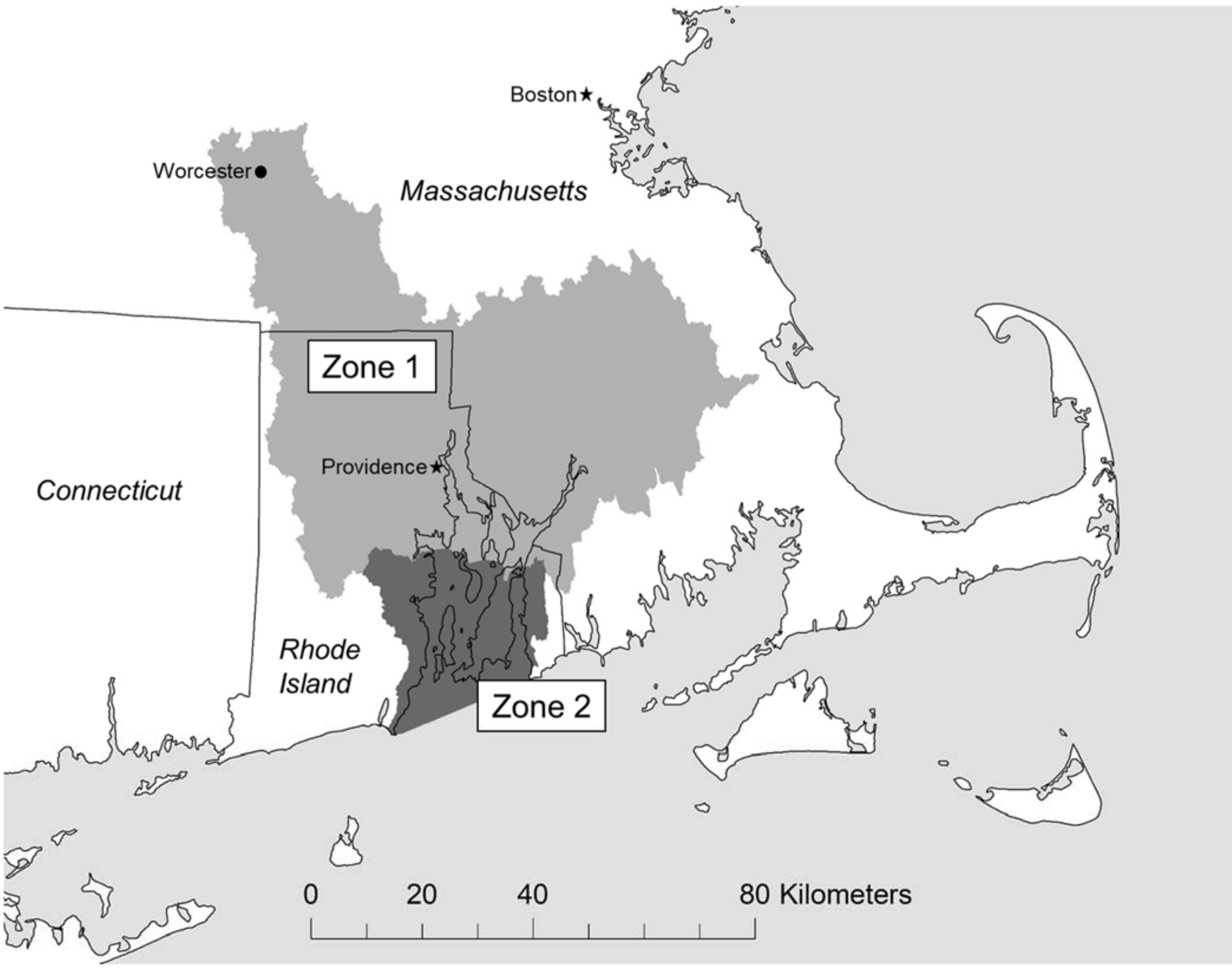

Figure 1. Narragansett Bay watershed study area

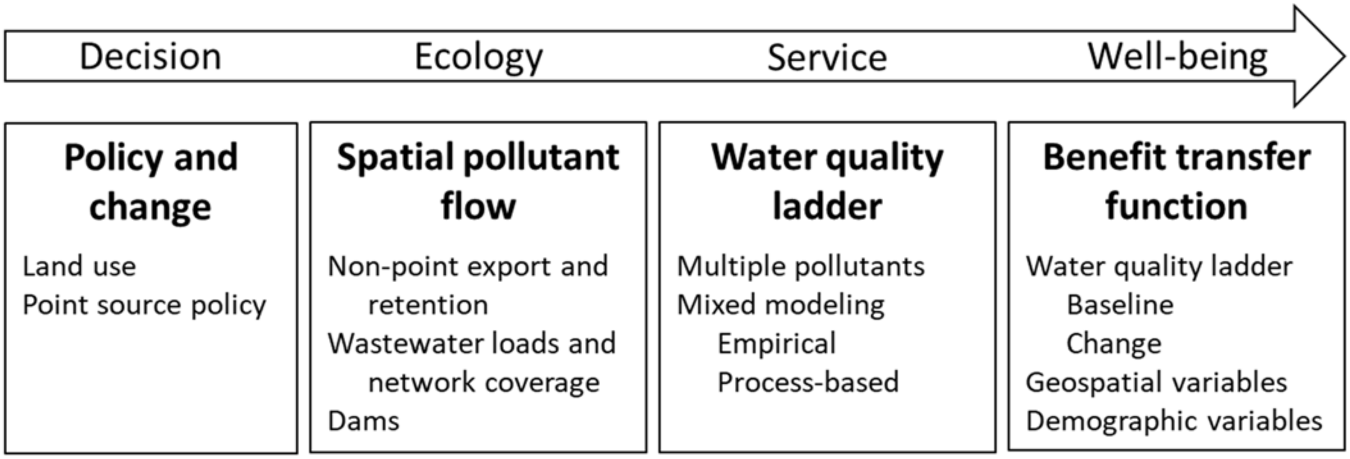

Figure 2. Model structure

Benefit transfer function

$$WTP_i = f(WQ, \Delta WQ, GEO, DEM_i, \overline{RES})$$

WTP – Willingness to pay/year/household (*i*)
WQ – Water quality index
GEO – Geospatial environmental variables
DEM – Demographic variables/household
RES – Research variables

Water quality index

$$WQ = \prod_{i=1}^{6} Q_i^{W_i}; \quad 0 \leq WQ \leq 100$$

Pollutant (Q_i)	Unit	Weight (W_i)
Dissolved Oxygen	# mg/L	.26
Enterococcus	cfu/100mL	.25
Total Nitrogen	# mg/L	.15
Total Phosphorous	# mg/L	.15
Total Suspended Solids	# mg/L	.11
Chorophyll-a	# µg/L	.08

Benefit transfer function variable descriptions

Variable	Variable Type	Description
Water Quality	WQ	Aggregate water quality index value in focal resource
Change in Water Quality	WQ	Change in water quality index value in focal resource
Proportion Ag Land	GEO	Ratio of agricultural land in adjacent counties
Area Ratio 1	GEO	Ratio of affected area versus adjacent counties
Area Ratio 2	GEO	Ratio of affected area versus adjacent HUC-10s
Relative Size	GEO	Ratio of affected shoreline versus affected area
Proportion Change	GEO	Ratio of length of focal resource vs substitutes
River/Estuary	GEO	Indicator of river or estuary
Region	GEO	Indicators of U.S. geographic region
Income	DEM	Median income (2007 US$) for affected pop
Use	DEM	Indicators for use types considered: fishing, swimming, boating, non-use value
Lump Sum	DEM	Indicator of payment format (lump sum or annual)
Research variables	RES	Fixed values associated with research design of sampled studies used to estimate value transfer function

Figure 3. Benefit transfer model

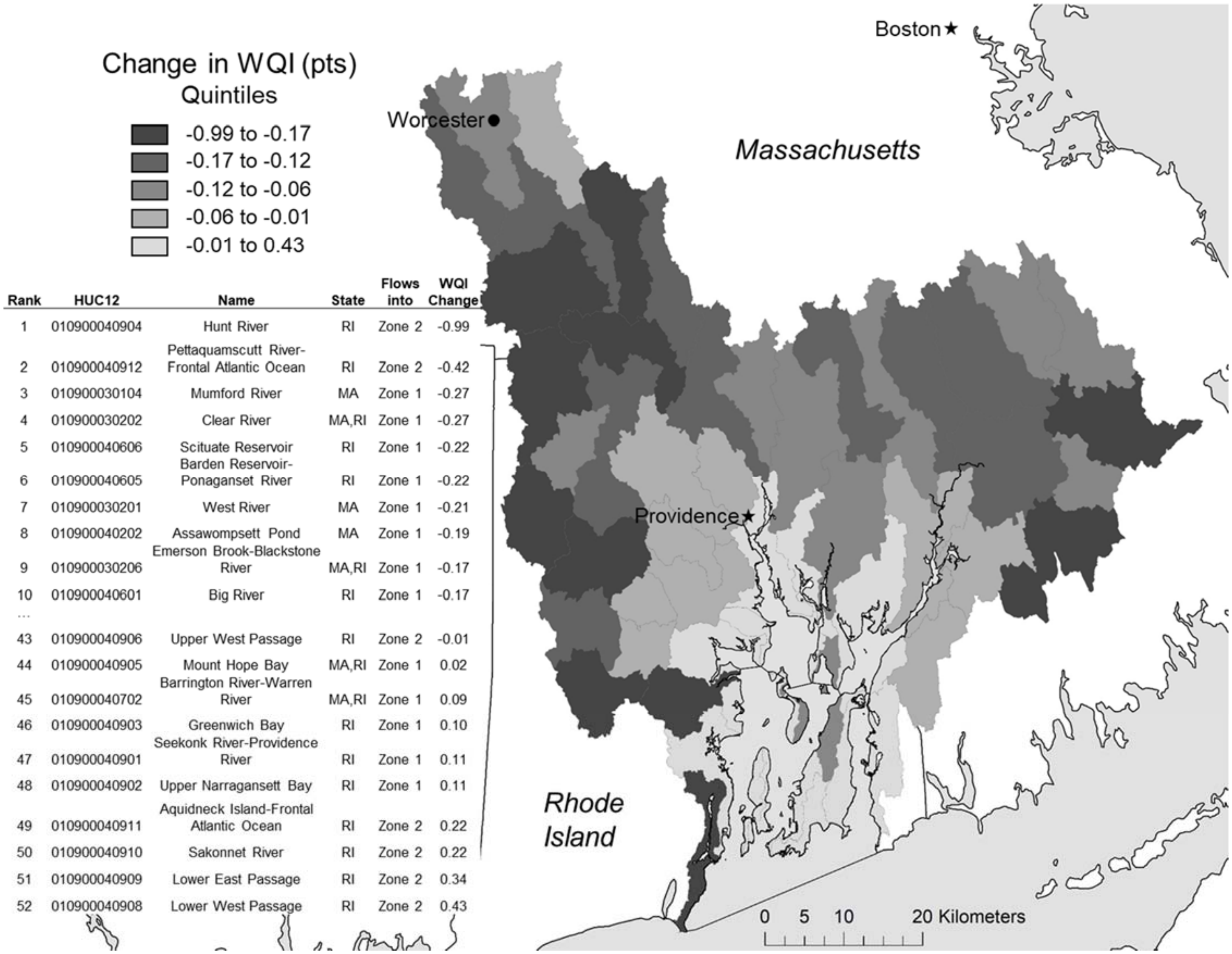

Figure 4. Marginal WQI change map for HUC 12 subwatersheds

Tables

	2001			2011		
	Zone 1	**Zone 2**	**Overall**	**Zone1**	**Zone 2**	**Overall**
Urban land cover (% of total)	32.6	39.7	33.2	35.5	41.4	36
Forested land cover (% of total)	58.5	42.8	57.2	56.3	41.5	55.1
Agricultural land cover (% of total)	5.6	8.1	5.8	4.9	7.8	5.2
Wastewater Treatment Facilities	24	5	29	23	5	28
Onsite Water Treatment Systems	-	-	-	39,121	29,290	68,411
Dams	-	-	-	338	14	352

Table 1. Drivers of point and non-point source pollution in the Narragansett Bay watershed

	2001		2011	
	Zone 1	**Zone 2**	**Zone 1**	**Zone 2**
Total Nitrogen (mg/l)	28 (2.8)	47 (1.6)	48 (1.6)	58 (1.2)
Total Phosphorus (mg/l)	38 (0.21)	40 (0.20)	58 (0.14)	39 (0.20)
Sediment (mg/l)	100 (17.5)	67 (52.6)	100 (19.5)	65 (54.2)
Dissolved Oxygen (mg/l)	84 (7.9)	97 (9.7)	99 (10.2)	100 (10.4)
Chlorophyll-A (ug/l)	10 (60.9)	19 (16.2)	31 (21.0)	36 (18.5)
Enterococcus (cfu/100ml)	98 (37.8)	98 (19.8)	97 (56.3)	98 (24.4)
Overall	57	64	75	70

Table 2. Water quality modeling results for 2001 and 2011

Scenario	Zone	Baseline WQ (100 pt scale)	Water Quality Change (pt)	Annual WTP per Household ($)	Total WTP ($Mil/yr)
2001 – 2011	1	56.5	18.1	59.6	50.6
	2	64.4	5.4	44.8	38.0
Remove all dams 2011	1	74.6	-6.3	-45.7	-38.8
	2	69.8	-2.5	-36.3	-30.8
Alternative WQI aggregation for 2001 – 2011					
WQI = f(TN,TP)	1	32.7	20.2	63.7	54.1
	2	43.5	4.0	42.1	35.7
WQI = f(TN,TP,DO,ChA)	1	41.3	22.6	64.7	54.9
	2	54.3	7.6	49.7	42.2

Table 3. Willingness to pay changes across scenarios

Appendix to "Decision support modeling for multi-attribute water quality in the Narragansett Bay watershed"

Additional main text tables and figures

Contaminant	Raw Value	Subindex Value
DO (mg/L)	DO ≤ 3.3	10
	3.3 < DO < 10.5	$-80.29 + 31.88*DO - 1.401*DO^2$
	10.5 ≤ DO	100
BC (cfu/100mL)	BC ≤ 50	98
	50 < BC ≤ 1600	98 * exp(-0.00099178*(BC – 50))
	1600 < BC	10
TN (mg/L)	TN ≤ 3	100 * exp(-0.4605*TN)
	3 < TN	10
TP (mg/L)	TP ≤ 0.25	$100 - 299.5*TP - 0.1384*TP^2$
	0.25 < TP	10
TSS (mg/L)	TSS ≤ 28	100
	28 < TSS ≤ 168	158.48 * exp(-0.0164*TSS)
	168 < TSS	10
ChA (µg/L)	ChA ≤ 40	100 * exp(-0.05605*ChA)
	40 < ChA	10

Adapted from (EPA, 2009)

Table A.1 – Subindex transformation curves

	2001		**2011**	
Loads (metric tons)	**Zone 1**	**Zone 2**	**Zone 1**	**Zone 2**
Non-point				
Total Nitrogen	1574	124	1592	125
Total Phosphorus	51.4	4.5	51.9	4.6
Sediment	41093	12672	45636	13052
Point				
Total Nitrogen	4879	271	2131	162
Total Phosphorus	433.2	43.5	274.7	44.5
Point + Non-point				
Total Nitrogen	6454	394	3723	287
Total Phosphorus	485	48	327	49
Sediment	41093	12672	45636	13052

Table A.2 – Loads

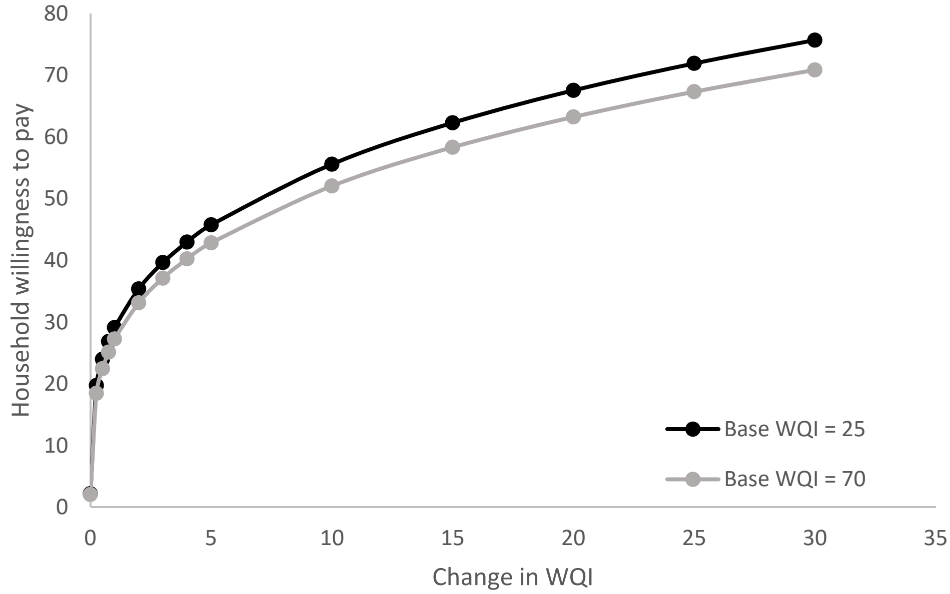

Figure A.1 – Benefit transfer function

Benefit transfer function parameters

We employ “unrestricted model two” from (Johnston et al., 2017) for use as the predictive meta-regression benefit transfer function in this study; see that study for more details on the derivation of this model. The scenario values for our retrospective analysis are given in Table A.3. All of the values for variables above the dotted line are specific to the desired scenario outputs of the case study in Narragansett Bay; values for variables below that line are set at the mean value for the sample of studies used in the meta-analysis. Household income was gathered from the 2010 U.S. Census for municipalities that intersect the Narragansett Bay watershed and deflated using the U.S. consumer price index (CPI) to 2007 USD for use in the transfer function. Simulated willingness to pay values using the transfer function were then inflated to 2017 USD using the CPI.

	Model		Non-log-transformed values				
			2001		2011		
Variable	**Coeff**	**(SE)**	**Zone 1**	**Zone 2**	**Zone 1**	**Zone 2**	**Description**
Ln_BaseQuality	-0.064	(-0.123)	56.5	64.4	74.6	69.8	Natural log of the baseline (status quo) water quality from which improvements would occur, specified on the 100-point water quality index
Ln_QualityChg	0.281	(0.106)***	-	-	18.1	5.4	Natural log of the change in mean water quality valued by the study, specified on the 100-point water quality index

Ln_Income	0.628	(0.375)*	57951	57951	57951	57951	Natural log of median household income (in 2007 $USD) for the market area
Ln_PropAgLand	-0.351	(0.095)***	0.04	0.0	0.0	0.0	Natural log of the proportion of the improved resource area (all adjacent counties) that is agricultural based on the NLCD
Ln_RelativeSize	0.052	(0.019)***	0.1	0.1	0.1	0.1	The natural log of the size of the sampled area (in square km) divided by the total area of all counties that intersect the improved water resource(s)
Ln_StudyYear	-0.478	(0.080)***	2017	2017	2017	2017	Natural log of the year in which the study was conducted (converted to an index by subtracting 1980, before making the log transformation)
ProportionChg	0.525	(0.189)***	0.52	0.48	0.52	0.48	The shoreline length of the water body as a proportion of all analogous (e.g., coastal) shoreline lengths
Voluntary	-1.296	(0.209)***	0	0	0	0	Indicator that WTP was estimated using a payment vehicle described as voluntary (0 = binding and mandatory payment vehicle)
OutlierBids	-0.429	(0.120)***	0	0	0	0	Indicator that outlier bids were excluded when estimating WTP (0 = study excludes outlier bids)
Non_Users	-0.455	(0.121)***	0	0	0	0	Indicator that the survey was implemented over a population of nonusers (0 = a survey of any population that includes users)
Swim_Use	-0.391	(0.220)*	1	1	1	1	Indicator for survey where swimming uses are specifically noted (0 = survey does not describe effects on swimming)
Boat_Use	-0.314	(0.183)*	1	1	1	1	Indicator for survey where boating uses are specifically noted (0 = survey does not describe effects on boating)
Game_Fish	0.303	(-0.207)	1	1	1	1	Indicator for survey where game fishing uses are specifically noted (0 = survey does not describe effects on game fishing)
River	-0.226	(0.128)*	0	0	0	0	Indicator for whether the studied system includes rivers (0 = no)
Multi_Body	-0.525	(0.145)***	0	0	0	0	Indicator for whether the studied system includes multiple water body types, e.g., lakes and rivers (0 = no)
Northeast_US	0.549	(0.249)**	1	1	1	1	Indicator for whether the survey included respondents from the USDA Northeast region (0 = no)
MedianWTP	-0.264	(-0.239)	0	0	0	0	Indicator for whether the study's WTP measure is the median (0 = mean WTP)
LumpSum	0.727	(0.136)***	0	0	0	0	Indicator for whether survey asked about a lump sum payment or annual payment (0 = payments on an annual basis over more than 5 years)
ChoiceExp	0.487	(0.210)**	0.11	0.11	0.11	0.11	Indicator for choice experiment survey (0 = any non-choice experiment method)
Thesis	0.557	(0.195)**	0.14	0.14	0.14	0.14	Indicator for studies developed as thesis projects or dissertations (0 = study not developed as theses)

NonParametric	-0.477	(0.126)***	0.43	0.43	0.43	0.43	Indicator for whether WTP was estimated using non-parametric methods (0 = study used parametric methods)
NonReviewed	-0.679	(0.171)***	0.24	0.24	0.24	0.24	Indicator for whether the study was not published in a peer-reviewed journal (0 = study published in peer reviewed journal)
Intercept	-2.281	(-4.225)					
R^2	0.63						
σ_ε	0.541						

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.3 – Benefit transfer parameters (adapted from Johnston et al., 2016)

Nitrogen

Model

Calibration

Phosphorus

Model

Calibration

Sediment

Model

Calibration

Dissolved oxygen

Multiple studies indicate that dissolved oxygen is linked to other water quality variables and that these drivers appear to vary by location and feature non-linear relationships (Prasad et al., 2011). In Narragansett Bay, there is strong interannual variability in dissolved oxygen concentrations, a persistent north-south gradient from low to high dissolved oxygen concentration, and generally lower dissolved oxygen observed in wet years (NBEP, 2017). We establish a predictive model of dissolved oxygen by estimating it as a function of other contemporaneously sampled water quality variables at six water quality gauges in Narragansett Bay maintained by the USGS. The gauges are: Blackstone - USGS gauge 01113895, Pawtuxet - 01116500, Moshassuck - 01114000, Ten Mile - 01109403, Woonasquatucket - 01114500, and Taunton - 01109060

Available data at these gauges allow us to characterize several potential predictors of dissolved oxygen, including water temperature, freshwater discharge volume, water pH, suspended solids, nitrogen and phosphorus levels, and fecal coliform concentrations (Table A.#). With this data, we specify a range of model specifications, including one emulating (Prasad et al., 2011), using site fixed effects to control for unobserved variation at each gauge station (Table A.#). We generally find that nutrient levels, temperature, and freshwater discharge are significantly correlated with dissolved oxygen. Because of limited spatially representative temperature and flow data throughout the bay, we opted for model 6 that predicts dissolved oxygen as a combination of total nitrogen and total phosphorus. The predictive model is: DO = 14.74 - 2.13*TN - 12.36*TP + 2.72*TN*TP

	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**
Temp (deg C)	399	13.3	8.2	0.0	29.5
Discharge (ft3/sec)	372	519	770	4	7650
DO (mg/L)	399	9.1	3.5	0.6	17.0
pH	396	6.8	0.5	5.2	8.6
Suspended Solids (mg/L)	160	10.5	7.5	0.0	51.0
Total Nitrogen (mg/L, unfiltered)	297	2.0	1.1	0.7	13.0
Total Nitrogen (mg/L, filtered)	52	1.2	0.3	0.8	2.2
Total Phosphorus (mg/L, unfiltered)	381	0.24	0.19	0.00	1.20
Total Phosphorus (mg/L, filtered)	118	0.06	0.07	0.01	0.49
Fecal Coliform (cfu/100mL)	266	619	1917	0	17000

Table A.#. Summary statistics for USGS gauge data used in dissolved oxygen regression

	Model 1	**Model 2**	**Prasad et al. (2011)**	**Model 4**	**Model 5**	**Model 6**
Temp (deg C)	-0.390***	-0.369***	-0.329***	-0.329***	-0.325***	
	-0.024	*-0.017*	*-0.014*	*-0.013*	*-0.013*	
Discharge (ft3/sec)	0.002*	0.001***	0.000*			
	-0.001	*0.000*	*0.000*			
pH	-0.151					
	-0.411					
TSS (mg/L)	0.021					
	-0.023					
TN (mg/L)	-0.829***	-0.384***	-0.578***	-0.566***	-1.171***	-2.126***
	-0.236	*-0.124*	*-0.118*	*-0.114*	*-0.245*	*-0.429*
TP (mg/L)	-0.38	-2.371***	-2.754***	-3.371***	-6.481***	-12.356***
	-1.169	*-0.839*	*-0.755*	*-0.693*	*-1.308*	*-2.285*

	(1)	(2)	(3)	(4)	(5)	(6)
FC (cfu/100mL)	0.000**	0.000**				
	0.000	*0.000*				
TN*TP					1.421***	2.723***
					-0.509	*-0.9*
Constant	15.671***	14.019***	14.844***	15.159***	16.214***	14.740***
	-2.833	*-0.412*	*-0.298*	*-0.244*	*-0.448*	*-0.789*
Observations	78	204	288	297	297	297
Number of site_no	2	2	3	3	3	3
Adjusted R-squared	0.89	0.81	0.77	0.77	0.77	0.29
AIC/N	3.45	3.89	3.92	3.92	3.90	5.05

Table A.#. Regression analysis of dissolved oxygen. Standard error in italics, site fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Chlorophyll a

Chlorophyll-a is the main photosynthetic pigment in phytoplankton and is readily measurable, making it a useful proxy for phytoplankton biomass and possibly for primary production in estuaries. There are many factors at play in predicting chlorophyll concentrations, including climatic and food web pressures, as well as the availability of nutrients, minerals, and other enabling conditions for growth (Ryther & Dunstan, 1971; Hoyer et al., 2002; Bbalali, 2013; Rai & Rajashekhar, 2014). In Narragansett Bay, changes in chlorophyll have been linked to two important stressors: nutrient enrichment and precipitation (NBEP, 2017). Chlorophyll *a* sampling is not conducted at the same USGS gauges we used in the dissolved oxygen modeling and the available data we could retrieve had narrower geographic coverage in the bay. Of these data sources, we used the Narragansett Bay Commission's monitoring program in the Providence River. This data extends from 2005 – present and includes many of the key predictors indicated as important in the literature (Table A.#).

	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**
Depth (m)	1197	0.6	1.0	0.0	24.2
Salinity (ppt)	1130	20.6	7.6	0.2	37.1
Temp (deg C)	820	16.1	7.2	0.5	32.7
pH	784	7.8	0.6	3.2	18.5
NO3NO2 (mg/L)	910	0.25	0.31	0.00	5.02
NO2 (mg/L)	910	0.008	0.009	0.001	0.116
NH3 (mg/L)	908	0.084	0.091	0.004	1.010
TP (mg/L)	910	0.12	0.10	0.00	0.83

Silicate (mg/L)	898	1.07	0.61	0.02	4.73
TN (mg/L)	609	0.78	0.32	0.28	3.09
TDN (mg/L)	909	0.56	0.39	0.10	4.32
ChA (ug/L)	1397	13.2	20.2	0.0	262.1

Table A.#. Summary statistics for chlorophyll *a* sampling from the Narragansett Bay Commission

The data includes PO4 (orthophosphate) versus total phosphorous. To convert between PO4 and TP, we use an approach from (Krumholz, 2012), that relies on estimates from (Nixon et al., 2008) that compares the long run average from 1975 to 2004 of observed inorganic PO4 and TP ratios in large tributary rivers in Narragansett Bay: the Pawtuxet, Woonasquatucket, Blackstone, Moshassuck, and Ten Mile rivers (see table 5.9 in (Nixon et al., 2008)). All of these rivers drain into the Providence River, so these datasets have close spatial overlap. The observed aggregate ratio of PO4 to TP in these rivers is 1 to 1.72, which we used to convert the NBC measurements to TP.

	LogChA (Model 1)	**LogChA (Model 2)**	**ChA (Model 3)**	**ChA (Model 4)**
Depth (m)	0.32**		5.57**	
	-0.14		*-2.77*	
Salinity (ppt)	-0.01		0	
	-0.01		*-0.14*	
Temp (deg C)	0.09***		1.15***	
	-0.01		*-0.11*	
pH	0.63***		9.60***	
	-0.13		*-2.31*	
TN (mg/L)	0.19	-0.05	-9.02	-13.24*
	-0.21	*-0.22*	*-6.85*	*-7.82*
TP (mg/L)	-1.95**	-3.84***	-207.28***	-184.31***
	-0.9	*-0.86*	*-50.34*	*-61.67*
TN*TP	1.72***	3.81***	202.82***	194.65***
	-0.63	*-0.66*	*-54.06*	*-68.57*
Constant	-4.01***	2.56***	-71.90***	24.55***
	-1.07	*-0.18*	*-17.3*	*-6.26*
Observations	544	609	544	609
AIC/N	10.56	15.29	8.02	8.364

Table A.#. Regression analysis of chlorophyll *a*. Standard error in italics. *** p<0.01, ** p<0.05, * p<0.1

The distribution of our chlorophyll data can be considered count data as is highly skewed in our sample, however the distribution of the residuals after a linear OLS regression appear to be normal, calling into question the value of log-transforming the dependent variable as has been done in other empirical research on chlorophyll *a* concentrations (Hoyer et al., 2002). We investigate a log and non-log dependent variable in the regression analysis (Table A.#). Models 1 and 2 are estimated with a log-linear generalized linear model with a poisson distribution and a log link function and robust standard errors. Models 3 and 4 are estimated with ordinary least squares with robust standard errors. We do not include fixed effects as all locations are very close to each other in the Providence River and monitored under the same sampling protocol.

As with the dissolved oxygen regression model, we observe that nitrogen and phosphorus play are strongly correlated with chlorophyll *a*, as are temperature, water depth, and pH. Similar data limitations also play a role in selecting model 4 for our predictive model, as well as residual normality and the practical challenges of predicting arithmetic mean values in the original scale when using a log transformation. The predictive model is: ChA = 24.55 - 13.24*TN - 184.31*TP + 194.65*NP

Enterococcus

Unlike the models for chlorophyll *a* and dissolved oxygen, the literature on fecal coliform (FC) and enterococcus, two closely linked indicators for pathogenic bacteria contamination in water, tends to focus less on linking to simultaneously sampled in situ water quality characteristics and more towards landscape level point and non-point source interventions directly. (Fisher et al., 2000) suggests that forest cover could increase FC concentrations from wild animals; however, the study is not robust statistically and is more qualitative in nature. (Frenzel & Couvillion, 2002) look at the effect of population density and sewer/septic systems on FC concentrations, finding that higher population density was associated with higher FC concentrations and sewered areas were associated with higher FC concentration than those served by septic systems, suggesting that the difference is driven by the fact that sewered areas had storm drains that discharge directly into streams and septic areas do not. (Sowah et al., 2014; Sowah et al., 2017) find a similar result in a multivariate regression with pooled data from spring, summer, and fall, while finding little evidence of a correlation with land use when including factors like impervious cover, agricultural land, and forested land. With pooled data across the year, the only statistically significant finding was that impervious cover tends to reduce markers of pathogenic bacteria.

Several other studies have hypothesize that land cover maps could have predictive power for estimating bacteria concentrations in adjacent waterbodies. (Tong & Chen, 2002) found positive and significant relationships of fecal coliform to commercial, residential, and agricultural land and a significant and negative relationship to forested land. (Walters et al., 2011) took a similar approach to (Tong & Chen, 2002) in an analysis in California estuaries using the HUC 12 level watershed as the analysis unit, with a multivariate regression analysis showing a significant positive relationship between bacteria and urban land cover. Salinity and rainfall were also largely significant across a variety of model specifications. Model fit was generally poor though, with an R^2 was between .11 and .23. Finally, (Vitro et al., 2017) features lots of mixed results with generally poor fit for land cover types besides urban land cover, similar to (Walters et al., 2011) and (Sowah et al., 2017), with urban land cover associated with greater bacterial contamination.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Enterococcus (cfu/100 mL geo mean)	380	105	553	5	6867
Enterococcus (cfu/100mL arith mean)	380	214	1142	7	14825
Temperature (deg F)	380	68	7	42	85
Prior 7 day precip (inches)	380	0.97	1.01	0	3.76
HUC12 Size (km2)	380	51	20	24	91
HUC12 Urban %	380	0.61	0.21	0.25	0.85
HUC12 Forest %	380	0.22	0.11	0.08	0.40
HUC12 Ag %	380	0.05	0.08	0.00	0.24
HUC12 WWTF %	380	0.57	0.30	0.04	0.97
HUC12 OWTS/km2	380	42	28	0	113

Table A.#. Summary statistics for aggregated data based on RI Department of Health bacteria sampling

Airport	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
PVD	1676	0.86	1.02	0	7.03
UUU	1676	0.72	0.9	0	6.25

Table A.#. Rainfall by zone at TF Green (PVD) and Newport (UUU) airports

	Total		Ratio to Total Area	
	Zone 1	Zone 2	Zone 1	Zone 2
WWTF (km2)	254.29	73.56	0.33	0.2

OWTS (#, #/km2)	39121	29290	50	80

Table A.#. Waste treatment systems within the network

We collected data from the Rhode Island Department of Health that included summer (May – Sept) sampling for enterococcus over the years 2006 – 2016 in Narragansett Bay (Table A.#). We supplemented this data with data on prior 7 day rainfall for the period 2006 – 2016 from the Iowa State University's environmental mesonet. From this source, we gathered daily precipitation data for the airports TFGreen (PVD) and Newport (UUU), which are in zone 1 and zone 2 respectively, and created a variable indicating a moving sum of 7 day antecedent rainfall approach based on (Walters et al., 2011) to create an indicator variable (1 = >0 rainfall; 0 = no rainfall). This data was attached to the geolocated enterococcus data based on whether it was closer to PVD or UUU (Table A.#.). Similarly, we added data on land cover to each observation based on the closest HUC 12 subwatershed land cover proportions in the classes urban, forested, and agricultural (Table A.#). These are the crosswalked aggregated land cover classes (classes from the 2011 National Land Cover Database):

- Urban (developed open space, developed low intensity, developed medium intensity, developed high intensity)
- Agriculture (pasture, cultivated crops)
- Forest (deciduous, evergreen, mixed, grassland)

Finally, we added data related to the wastewater network coverage (coverage area within nearest HUC 12 divided by HUC 12 overall area) and the density of septic systems in the nearest HUC 12 (#/km^2). These layers were sourced from the Narragansett Bay Estuary Program (Table A.#).

Data on enterococcus is generally not randomly sampled as noted by (Vitro et al., 2017) as sampling tends to be done for specific reasons, like beach recreation or measuring progress in areas with poor water quality. As a result, our regression specifications were again partially limited in what we can use by the need for out of sample prediction throughout Narragansett Bay. We include land cover (urban, forest, agriculture), percentage of adjacent HUC 12 subwatershed served by a wastewater treatment network, watershed size (km^2), septic density, prior 7 day rainfall, and temperature in the regression models, but are forced to remove temperature in our final predictive model due to a lack of a representative mean value for each zone in the bay.

We employ a log transform of the dependent variable following guidance in the literature in a generalized linear regression model, where the dependent variable is alternatively considered as a geometric or arithmetic mean depending on the model specification. Geometric means are used to avoid zero-inflation in bacteria sampling data analysis (Vitro et al., 2017). Like with the chlorophyll *a* modeling, we estimate all models here using a generalized linear model with a poisson error structure and log link function with robust standard errors.

	Geo Mean 1	**Geo Mean 2**	**Geo Mean 3**	**Ari Mean 1**	**Ari Mean 2**
Temperature (deg F)	-0.03	-0.03		-0.01	
	-0.03	*-0.02*		*-0.03*	
Prior 7 day precip (inches)	0.55***	0.55***	0.55***	0.65***	0.65***
	-0.17	*-0.17*	*-0.17*	*-0.18*	*-0.18*
HUC12 Size (km2)	0.01			0.03	
	-0.02			*-0.02*	
HUC12 Urban %	20.29	20.47*	20.88*	13.21	14.35
	-12.97	*-11.92*	*-12.19*	*-15.76*	*-11.68*
HUC12 Forest %	-0.32	-0.39	-0.21	-5.59	-4.91
	-8.29	*-8.16*	*-8.16*	*-9.19*	*-7.63*
HUC12 Ag %	-1.26	2.25	2.19	-14.03	-5.58
	-13.59	*-9.26*	*-9.28*	*-15.11*	*-9.91*
HUC12 WWTF %	-18.83**	-18.78**	-19.32**	-18.90*	-18.86**
	-8.64	*-8.16*	*-8.29*	*-10.65*	*-8.4*
HUC12 OWTS/km2	-0.08**	-0.08**	-0.09**	-0.10*	-0.10***
	-0.04	*-0.04*	*-0.04*	*-0.05*	*-0.04*
Constant	6.93	7.05	5.41	11.74**	11.65**
	-5.28	*-5.36*	*-4.96*	*-5.73*	*-4.83*
Observations	380	380	380	380	380
AIC	143336	143868	145084	298566	304342

Table A.#. Regression analysis of enterococcus. Standard error in italics. *** p<0.01, ** p<0.05, * p<0.1

We find across models qualitatively similar results to several recent studies, including a weakly positive association between urban land cover and enterococcus concentrations and no significant effects for other land use, as well as a strongly positive correlation with recent rain events (Table A.#). More wastewater treatment network coverage and more densely distributed septic systems are associated with a decrease in bacterial concentrations. This is an interesting result in that wastewater treatment networks' ability to reduce bacterial contamination of adjacent waterbodies is often done by eliminating combined sewer overflow systems and increasing treatment capacity during acute precipitation events, and not necessarily by expanding coverage. We select model 3 for our final predictive model which varies by zone based on the landscape characteristics included in the regressions. We do not vary any of the predictors in this model across scenarios aside from land use.

Zone 1: $E = \exp(-4.99 + 20.88*Urb - 0.21*For + 2.19*Ag)$

Zone 2: $E = \exp(-5.26 + 20.88*Urb - 0.21*For + 2.19*Ag)$

Flow modeling

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Dam modeling

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[i] The weighted geometric mean function used for aggregation has been qualitatively shown to have more consistent properties than other aggregation approaches based on first principles (Walsh & Wheeler, 2012), though more rigorous testing is warranted to see how it corresponds to actual use patterns.

[ii] Recent research is changing this and this could soon be a ready addition to the IAM. (Maavara et al., 2015) appear to be the first to derive and parameterize a process-based approach for estimating P retention by dams using a dataset of 155 dams.

[iii] While this was beyond the scope of our study, see (Toft et al., 2013) for an example of linking some of the process-based models used in this IAM to a marine water quality model developed in Puget Sound.

[iv] The maximum possible score for enterococcus is 98 due to the uncertainty of analytical procedures for counting bacteria (Cude, 2001).

[v] Observed values for several of the predictors remained constant between 2001 and 2011, largely due to data gaps that did not allow us to characterize changes through time. These included onsite water treatment system density, wastewater network coverage, and prior 7 day rainfall. As such, the predicted outputs are driven entirely by the land use categories.

[vi] "Natural areas" includes the following NLCD land cover classes: Barren Land, Deciduous/Evergreen/Mixed Forest, Shrub/Scrub, Grassland/herbaceous, Woody Wetlands and Emergent Herbaceous Wetlands.

[vii] Non-marginal change tends to break assumptions of water quality models, however smaller scale change tends to run the risk of losing a significant signal in the estimates (Guswa et al., 2014), therefore the analysis resolution of marginal change maps need to carefully weigh the two and often is best presented at the watershed scale where most hydrological models are derived.

[viii] See (Johnston & Rosenberger, 2009) for a review of methodological and practical considerations for benefit transfer and (Guswa et al., 2014) for a similar review of hydrology in the context of applied decision making.

[ix] With sufficient parameter variation rank ordering could easily shift between conservation options in our marginal mapping exercise, which has been shown to have the potential to easily erode the efficiency of a conservation program (Johnson et al., 2012).