USFWS National Wildlife Refuge Wetland Ecosystem Service Valuation Model Phase 1B Final Report

An Assessment of Ecosystem Services Associated with National Wildlife Refuges

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Executive Summary

In recent years, public benefits from ecosystem services have been the focus of increasing attention from scientists, managers, and stakeholders. The measurement of the non-market benefits such as clean water or flood protection that the public receives from ecosystem services is known as ecosystem service valuation. Primary valuation studies use original data to measure these values and are the ideal approach. Benefit transfer methods have been developed as a low-cost and rapid alternative to primary valuation studies. Benefit transfers are methods where ecosystem service values that have been previously measured by primary valuation studies are used individually or in a group to infer the value of benefits at an unstudied site. Meta-analysis benefit transfer is a robust type of benefit transfer that typically uses a statistical model to incorporate information from multiple primary valuation studies for benefit transfer.

The focus of our research is to develop improved techniques for conducting meta-analysis benefit transfer in order to gain a better understanding of the ecosystem service values associated with wetlands in the USFWS National Wildlife Refuge (NWR) System. In phase 1a of our research we examined how an existing, peer-reviewed meta-analysis model can be used to estimate public benefits from water quality provisioning, flood and storm surge protection, and habitat for commercial fish species that can be attributed to NWR wetlands in four case study NWRs. Phase 1a also included an assessment and quantification of the carbon stocks and associated values of carbon storage at four case study NWRs.

In phase 1b of our research, presented in this document, we conduct a novel meta-analysis restricted to wetlands of the contiguous US, and we expand our analysis of existing meta-analyses by other authors to provide a broad comparison. To illustrate this new approach we focus our novel meta-analysis on the estimation of benefits that wetlands contribute to water quality and flood and storm protection services. We developed a new statistical approach to enhance the accuracy and flexibility of our meta-analysis while maintaining a systematic approach. Using the new modeling method and a new domestic-oriented wetland valuation database, we estimate ecosystem service values at the four case study refuges. Results indicate that wetlands near large populations and with few adjacent wetlands are among the most valuable. Populations with higher incomes are also likely to place a higher value on wetland ecosystem services. Our model also largely agrees with other models that water quality provisioning is often more valuable than flood control and storm protection, yet in many instances (contrary to the other more restrictive models we reviewed) this relationship is found by our flexible model to be reversed. For example, water quality provisioning is found to be less valuable than flood control and storm protection services at the two larger refuges, Blackwater NWR and Okefenokee NWR. Our results broadly indicate decreasing returns to scale as wetland acreage increases, a finding consistent with the comparison models.

Concerns remain in the scientific and public policy communities about the accuracy of benefit transfers. Accordingly, we advise that estimated values based on meta-analysis benefit transfers are valid for making ordinal comparisons across different wetlands or user populations. This approach avoids over-reliance on potentially imprecise values based on small samples and sites with heterogeneous characteristics and user populations. Comparisons of relative differences among estimates and methods will be useful in interpreting the importance of ecosystem service values that often can vary spatially and temporally. Future research is needed to: 1) expand the current model by including a wider variety of primary valuation studies focusing on a broader group of wetland ecosystem services; 2) develop useful applications of these values and test their generality in decision making. For example, these estimated values could be useful along with other information regarding which refuges could be expanded to increase the value of multiple ecosystem services. Ranking the relative public benefits of future wetland acquisitions against the real-estate costs of those acquisitions might be effective in determining landscape-level plans for protecting corridors or providing sustainable habitats under different future demographic or climate scenarios. Novel primary valuation studies of common but under-studied wetlands are also an important means for enhancing our understanding of these important public benefits and enhancing the accuracy of the next iteration of benefit transfers.

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Introduction

This document is intended as a follow-up of the initial assessment of wetland ecosystem services, "National Wildlife Refuge Wetland Ecosystem Service Valuation Model, Phase 1 Report" by the same authors. The purpose of this update is to provide additional insights into the process and results of rapid ecosystem service valuation. The rapid valuation technique we use, Meta-Analysis Benefit Transfer (MABT), offers researchers a systematic way to test hypotheses about the causes of variations in ecosystem service values as well as for forecasting ecosystem service values. We are particularly interested in the potential for using the MABT for producing forecasts of ecosystem service value; this document is intended in part to provide a fuller picture of the variability of predicted valuation results from various published meta-analysis studies. We also provide a novel meta-analysis of our own, which is intended to target water quality provisioning and flood control and storm protection services of wetlands in continental National Wildlife Refuges. We develop and estimate a novel, parametric locally weighted least squares regression model that we refer to as PLWLS. The purpose of the new model is to enhance the efficiency of forecasts.

A wide variety of policy applications ranging from low stakes local decisions to high stakes international policies require estimates of the benefits to the public provided by various ecosystems. In order to compare these benefits to the benefits of conventional, private-market goods, quantification is in terms of monetary value. Benefit transfers (BT) are a valuation approach particularly apt for low-stakes decision making contexts that tend to exclude quantitative non-market ecosystem service values. Low-cost, rapid estimates of the economic value of wetland ecosystem services can be produced via benefit transfer with existing wetland ecosystem service meta-analysis (MA) models, but the accuracy of these models compared to primary studies is poorly understood. Compounding uncertainty about the appropriate uses of benefit transfer value estimates obtained from meta-analysis models is the uncertainty that exists with regard to the correct methodology for calculating benefit transfer estimates. Specifically, peer-reviewed guidance is lacking with regard to the best practices for implementing a meta-analysis benefit transfer (MABT), in particular, when several existing meta-analyses are available.

The use of MAs for prediction of a population's willingness to pay (WTP) for ecosystem services from wetland landscapes has been, to the best of our knowledge, confined in the peer-review scientific literature to the very studies that design and estimate an MA model. The process of creating a database of studies, coded for all relevant explanatory variables and estimating a model requires a considerable amount of time and expertise. As MABT value estimates are especially low in cost to produce, a natural extension of the MABT literature is an analysis of the choices faced by an independent analyst with

limited resources that prevent the estimation of a novel, state-of-the-art MA model. When resources allow the creation of a targeted MABT model, questions still remain regarding valid applications of the model.

While we interpret the dependent variable in these studies as a measure of Hicksian surplus, or willingness to pay, important cautions have been raised in the literature about the appropriateness of such an interpretation of the dependent variable. Welfare measure consistency, discussed in Smith and Pattanayak (2002) and Bergstrom and Taylor (2006) and again in the review paper of Nelson and Kennedy (2009), requires (under a strict interpretation) that the studies comprising the meta-data in the original MA have the same welfare measure. This feature is lacking in all three MAs used for BT herein. A similar concept, commodity consistency, requires that the services or goods valued in each observation of the MA also be identical. The need for a greater understanding of ecosystem service values combined with the extensive heterogeneity in primary valuation studies has led to compromises on the part of MA researchers who essentially may choose only two, at best, of the following three desirable attributes: a large dataset, welfare measure consistency, or commodity consistency. Bayesian MA studies that take advantage of small samples tend to focus on the latter two (Leon-Gonzalez and Scarpa 2008; Moeltner, Boyle, and Paterson 2007; Moeltner and Woodward 2009), while the studies in our analysis focus on a large dataset by including a variety of valuation approaches and services. We rely on dummy variables to achieve commodity and welfare measure consistency.

Meta-analysis methods were originally developed by Glass (1976) for evaluating the effect size of treatments in the field of education research. The first ecosystem service meta-analysis studies were published in the late 1980's and early 1990's (Walsh, Johnson, and McKean 1989; Smith and Kaoru 1990a; Smith and Kaoru 1990b). A sequence of wetland ecosystem service studies that focused on the landscape rather than the consumer have been published more recently (i.e., Woodward and Wui 2001; Brander, Florax, and Vermaat 2006; Ghermandi et al. 2010). These studies are convenient for answering questions about management of wetland landscapes because the dependent variable is willingness to pay per acre rather than willingness to pay per person as was the case with earlier nonmarket valuation meta-analysis studies.

Benefit transfer methodologies such as benefit point transfer preceded MABT by more than a decade (Johnston and Rosenberger 2010). Benefit point transfers are the simplest type of benefit transfer where a measure of welfare obtained by studying one site is used as a value for a different site as if it were measured there by the primary valuation study. Commonly, the site where the original study was performed is referred to as a *study site*, while the site where the value is applied is referred to as a *policy site* (Rosenberger and Loomis 2000). A variety of techniques have been developed to transfer one or more study results from *study sites* to a *policy site*; while results have been mixed, studies reviewing a variety of transfer methodologies have often concluded that MABT *can* lead to lower transfer error than benefit

transfer methodologies that make less systematic use of the available data, but that existing MA studies do not meet the necessary criteria and thus may perform quite poorly (Rosenberger and Stanley 2006; Johnston and Rosenberger 2010). However, MABT models make the most systematic use of available data, a highly desirable feature in empirical studies.

In this paper, we examine the flows of selected ecosystem services from wetlands in Arrowwood National Wildlife Refuge (NWR), North Dakota; Blackwater NWR, Maryland; Okefenokee NWR, Georgia; and Sevilleta and Bosque del Apache NWRs, New Mexico. The Sevilleta and Bosque del Apache NWRs are modeled as a single unit because of their proximity to one another within a single ecoregion along the Rio Grande River and the availability of extensive data from the Sevilleta's Long Term Ecological Research (LTER) project. The choice of sites is intended to contrast major types of wetlands of the contiguous United States. Salinity, precipitation, temperature, and distance to ocean are examples of physical variations across these sites. Variability across the sites in income distribution, population density, and culture reasonably well represent the range of diversity that could be compared quickly within the scope of our analysis. All values are adjusted for inflation to 2010 US dollars using the US Bureau of Labor and Statistics CPI Inflation Calculator. Landcover data for the Brander et al. (2006) meta analysis primarily come from the NLCD 2006 dataset (Xian et al. 2009) while landcover data for the Ghermandi et al. (2010) meta analysis come from the USFWS National Wetlands Inventory database (USFWS 2011), due to the definitions used in these studies to distinguish among wetlands.

Our analysis focuses on two specific wetland-related ecosystem services, water quality provisioning and flood control and storm protection. In this report we typically refer to the combined services of flood control and storm protection as simply flood control, as the valuation studies in our meta-analysis dataset include coastal storm protection services focused on flooding from storm surge. Similarly, for simplicity, we refer to water quality provisioning simply as water quality. The provisioning of increased water quality and flood control affect downstream (or inland) populations that are off-site. Because the pre-existing MA studies we consider do not require an estimate of the population benefitting from the services and the two services we consider affect populations in a spatially complex manner, these services can be valued in a much more straightforward manner with a MA that has a dependent variable normalized by wetland surface area. Recreation benefits, especially in the context of NWRs which have visitation data, might be more accurately valued using MAs that have the dependent variable welfare measure normalized by person, trip, or household. Recreation benefits are not modeled in this study.

Because several relevant meta-analyses of wetland ecosystem services can be found in the peer-reviewed academic literature (e.g., Woodward and Wui 2001; Brander et al. 2006; Ghermandi et al. 2010), we begin our benefit transfer valuation experiment by exploring the options for predicting

willingness to pay for a landscape that provides ecosystem services using each of these studies. Due to the logarithmic transformation of the dependent variable common in ecosystem service meta-analyses, no simple method exists for computing benefit transfer expected values from stochastic MA models. Accordingly, to estimate the distribution of willingness to pay, we simulate the dependent variable's distribution, allowing for estimation of quantiles and the mean associated with each existing MA and study site. Because we have three similar MA models pertaining to wetland ecosystem services, we implement a forecast combination approach in order to efficiently combine data from each of the existing meta-analyses considered.

The heterogeneity of the primary data for each MA model used in our analysis makes unclear whether the best interpretation of predicted values is that they are the value of a service or the value of a wetland that provides a service. In choosing the contingent valuation methodology (CVM) or stated preference approach, where applicable, the most apt interpretation is that we are valuing a wetland that provides a service. A review of many of the CVM studies that are referenced by each MA and of the stated preference studies in our own MA dataset indicates that the valuation questions is typically focused on a particular wetland extent and the respondents are notified of the most important services provided by that wetland. The units of the dependent variable in the existing MA models, WTP/area/year, also suggest that the appropriate interpretation of the MA model dependent variable is associated with a wetland that provides ecosystem services.

The validity of using existing MA models for MABT depends on the required accuracy of the intended use of the results (Sargent 2010). An understanding of the features of each study is useful for developing a qualitative sense of the expected accuracy of each model. The validity of MABT values for land-use and public policy decisions is still a matter of debate due to uncertainty about the accuracy of transfers. Much of the focus of this study is not on the validity of BT estimates for policy decisions, but on the content validity (Bishop 2003) of value estimates obtained with an MA model. In other words, a primary purpose of this study is to help establish best practices for using existing MAs for MABT.

A key theme that emerges in the steps detailed below is the reduction in accuracy and simplifying assumptions for our analysis that are required due to unavailability of a thorough statistical description of each published MA model. Below, we first briefly discuss important features of wetlands in each NWR study site and our qualitative expectations of the value of several ecosystem services. Next, we discuss the method followed and data necessary for implementing each MA model and provide a discussion of how one might best proceed when faced with incomplete modeling information. Then we present the results of each MABT dependent variable simulation. We end with a discussion of the results and implications for future MA studies.

In addition to analyzing the performance of existing MA studies, we develop a novel MA database and implement two estimation strategies. The first strategy is the familiar OLS model and the second strategy is the PLWLS estimator that we develop, primarily in the appendix. The unique MA database that we develop focuses entirely on wetlands in the contiguous United States. While we are most interested in flood control and water quality services, we include a variety of other services and necessary controls in order to obtain better inference on parameters common across all observations, such as the effect of a population's income. An important contribution of our MA model is that we normalize the dependent variable, aggregate willingness to pay, by both acres valued and the population over which the welfare measure is aggregated. We chose such a normalization and also included the population over which results are aggregated as an exogenous variable as it became evident in the course of constructing the MA database that aggregating a welfare measure is too sensitive to potentially arbitrary assumptions to rely on a reduced form model that omits details about how the analyst chose to aggregate the welfare measure. Specifically, we found that surface area and population were the most important aspects of the modeling process that are best treated as analyst imposed decisions for the purpose of answering specific questions (e.g., What are the benefits of the water quality provisioning services associated with specific wetlands indicated on a map to the residents of the state that contains the wetland?). An important implication of this approach is apparent in how we interpret, discuss, and treat the dependent variable. The alternative interpretation of the MABT model is that we are forecasting the results of a hypothetical primary valuation study, not that we are directly predicting a welfare measure that can be sensibly communicated without also describing the methodology by which the value was measured.

The appropriate interpretation of the dependent variable is an important and nuanced issue that in our view has received too little attention in the ecosystem service MABT literature. In all studies in this field that we are aware of, the dependent variable is essentially treated directly as an estimate of an economic welfare concept. We interpret the dependent variable somewhat differently, as the resulting welfare estimate obtained via a primary valuation study. For forecasts of the dependent variable the estimated value is fundamentally the predicted result of a primary valuation study. Due to the possibility of generating predictions from unlikely or even nonsensical combinations of services and methods, such an interpretation better highlights the context of the WTP estimate and implies the appropriate means for criterion validation (i.e., conducting a primary valuation study to serve as a comparison). For example, via MABT one might forecast the value estimated by a travel cost study that values commercial fishing at a temporarily flooded forested wetland site where no commercial fishing operations exist; criterion validation via a primary valuation study of this predicted value is not feasible or sensible. Simulations of the results of such a study with MABT are feasible but the results fail a basic test of content validity. Similarly, the practice of coding methodological variables at their sample means and predicting a single

number suggests an unusual (and typically non-linear) hybrid of studies that would defy criterion validation efforts; alternatively, simulating a number of realistic primary valuation studies (coding methodological dummy variables as 1's or 0's) and using a weighted average to combine the results is more consistent with the original data and amenable to criterion validation with future primary valuation studies.

In the sections below, we first develop the basic methodology by which we examine existing MA studies and the novel database that we have constructed. Secondly we review the data that are required for the various methodologies we describe. Next we provide the final results and a discussion of those results followed by some general conclusions. An appendix is included at the end where we develop the PLWLS estimator in detail.

Methods

The methodology section is organized into 4 parts which each describe a means for analyzing valuation data. These data analyses are intended to both shed light on ecosystem service values estimated with secondary data and the performance of MA models that are used to analyze and estimate those values. First we examine the relative sampling performance of existing, published wetland valuation MAs. Second we present a straightforward OLS model that we will implement with a novel dataset of our own construction. The third component of our methodology is the introduction of a new estimation procedure intended to increase the efficiency of MABT forecasts while avoiding *ad hoc* analyst resampling. Finally we briefly discuss a means for simulating out-of-sample forecast performance that can be used to compare the performance of OLS with our new estimator.

Models from the Literature: Constructing Confidence Intervals and Forecast Combination

In our initial analysis, we conduct three separate MABTs, based on the published MA models of Woodward and Wui (2001), Brander et al. (2006), and Ghermandi et al. (2010). Each of these studies reports an estimated relationship between per acre (or per hectare) willingness to pay and regressors related to characteristics of the wetland (e.g., size), the surrounding population and geography (e.g., population density), the methodology used to generate the estimate (e.g., contingent valuation, travel cost), and study quality (only in Woodward and Wui 2001). Table 1 contains a list of explanatory variables included in each of the three pre-existing meta-analysis models. We divide these variables into categories similar to the divisions of explanatory variables in each study. All three of these meta-analysis

studies include a diverse assortment of primary valuation studies that include several wetland ecosystem services and represent all populated continents. The first step in our method is a parametric Monte Carlo simulation of the dependent variables of interest for each meta-analysis. The second step is a forecast combination procedure that combines the results from the first step for each service at each refuge. We develop these methods in the context of MABT in order to shed light on questions about how one might use existing MAs for MABT. We are particularly interested in how one might assess the statistical properties of MABT forecasts with only the published summary of a model and dataset available.

Monte Carlo Simulation of Distribution

As mentioned above, the popularity of using logged dependent variables necessitates a more complex approach such as bootstrapping or Monte Carlo simulation to capture the effects of curvature of the exponential function within the expected value operator (Wooldridge 2002). In order to properly model the exponential function with limited information about the original sample, we simulate the entire distribution of each dependent variable forecast using a parametric Monte Carlo simulation. The bootstrapping approach would be desirable, but is not possible without the original sample.

Limited information reported in the three meta-analyses makes it difficult to accurately estimate confidence intervals associated with the expected WTP estimates without relying on additional assumptions. Using estimated coefficients and standard errors, we use a Monte Carlo simulation to obtain a distribution for the dependent variable. The original MA studies we employ do not report the full covariance matrix of the estimated parameters, so we assume zero covariance between parameters, resulting in a diagonal variance-covariance matrix for the regression parameters.

The basic algorithm for our parametric Monte Carlo simulation, implemented in Matlab, is to draw a pseudo-random vector of parameter values from each meta-analysis using a joint normal distribution with mean and variance equal to the estimated parameters reported in each study. We multiply each of the constant value regressors from Tables 2 - 5 by the appropriate joint normal randomly drawn parameter and the sum of these products is exponentiated by the base of the natural logarithm. The process is iterated one million times for each meta-analysis, each wetland NWR and each of the two services considered, resulting in 24 vectors with length equal to one million containing log normally distributed WTP estimates. We compute the mean of each series and the variance of the mean by regressing each vector on a 1 million element column of 1's and obtaining the OLS estimated parameters and associated homoskedastistic variances. Also, from each of the 24 sorted vectors we obtain quantiles representing the 5th, 50th, and 95th percentiles.

The parametric Monte Carlo simulation is useful because it provides us with a means for estimating the variance of each WTP estimate. The popular alternative procedure typically requires an estimate of the standard error of the residual (Wooldridge 2002), which was not available for all the MAs we consider. Our assumption that the covariances of the parameters are all zero may lead to substantial error in the estimated variance of the dependent variable; in particular this may be a problem when used with a model based on a small sample. For example, if we observe two explanatory variables that have positive values and we randomly draw positive estimated coefficients that should have negative covariance but this covariance is assumed to be zero, the resulting sum of the product of each variable and its coefficient will be biased upwards. The purpose of our experiment is to explore how to implement MABT using a suite of existing models from published summaries of the original results. Obtaining each dataset and running full-sample diagnostics would be preferable, but as rapidly growing interest in ecosystem service values outpaces funding to implement primary valuation studies to estimate these values, the usefulness of existing models to produce the lowest cost quantitative estimates is a natural question.

Forecast Combination

We use the simulated distribution of WTP described above to combine the three separate point estimates for each simulated study into a single value via an inverse variance weight approach (DerSimonian and Laird 1986; Borenstein et al. 2009). The forecast combination literature suggests an inverse variance weighting approach often leads to improved forecast performance (Smith and Wallis 2009). Accordingly, we take a weighted average of the three median values estimated from each meta-analysis for each service at each refuge. This inverse variance weighting is identical to implementing an efficient generalized least squares regression (Wooldridge 2002) where the model includes only an intercept and we possess known variances. The weighted average of WTP for site i and service j, can be seen in equation (1), where subscripts i and j index the site and service and subscript k indexes the meta-analysis used for the WTP estimate. Summation is over k=1,…,3 for the three meta-analyses.

$$\overline{WTP}_{ij} = \frac{\sum[\frac{1}{V_{ijk}} med(WTP_{ijk})]}{\sum[\frac{1}{V_{ijk}}]} \qquad (1)$$

In equation (1) we choose the point estimate or median of the distribution as a conservative central estimate of WTP but use the estimated variance of the sample mean of the one million Monte Carlo draws. The use of a median is consistent with predicting the outcome of a referendum vote, where the magnitude of any individual's WTP is relevant to the extent that it tells us how that individual will vote for a policy. The median also reduces the influence of large outliers relative to the mean.

Additionally, as the logarithmic transformation of WTP ensures positive values across the simulated distribution (censoring of non-positive WTP estimates), the use of the median measure of central tendency opposes to some extent the effect of a truncated predicted distribution(i.e., negative values are not allowed when the dependent variable is in log form). Ultimately, the use of the median in place of the mean is particularly compelling with inefficiently estimated models as the mean may be very large due to outliers. In equation (1), each weight is then the inverse of the simulated variance of the mean associated with that observation. The sum is normalized by the sum of the inverse variances associated with each meta-analysis model. Alternatively, inverse variances can be interpreted as precision estimates and each weight is the share of that observation's precision among the three MAs.

In addition to the inverse variance or precision weighted average, we also estimate a conventional, evenly weighted average. We do so in order to highlight the influence of simulated variances on the final estimate of WTP. We choose the median as our initial estimate of willingness to pay in the spirit of obtaining conservative estimates. For instances where willingness to accept is the appropriate construct (e.g., when consumers are deprived of the benefits of an ecosystem service to which they have a legal right), the larger mean rather than median of each simulated distribution may be more appropriate.

OLS Regression with a Novel MA Dataset

In order to allow comparison between our MA dataset and existing datasets, we provide an OLS regression that is largely consistent with the existing wetland meta-analyses. Diverging somewhat from existing wetland MAs, we utilize the dependent variable normalized by both surface area in acres and the population over which individual welfare estimates were aggregated in the primary valuation study. Equation (2) is the basic form for our linear MABT forecast model where the dependent variable, $\log(WTP_i)$ is the natural logarithm of the estimated aggregate willingness to pay divided by the population and acreage counts associated with the aggregate value for observation i.

$$\begin{aligned}\log(WTP_i) = \beta_1 &+ study\backslash site_{vars\ i} * \beta_2 \\ &+ methodological_{vars_i} * \beta_3 \\ &+ context_{vars_i} * \beta_4 \\ &+ e_i\end{aligned} \tag{2}$$

In equation (2), *study/site*$_{vars}$ is a set of study descriptor variables, including the study area and the count of the study population over which the value estimate is aggregated; both of these values are used in the normalization of the dependent variable. We specifically label this group of variables to draw attention to the fact that the acres and population over which valuation is applied are characteristics of a

primary valuation study and often not natural characteristics of a landscape or geographic context. *Methodological*$_{vars}$ includes dummy variables for the service valued and indicators of whether the valuation approach is stated preference, revealed preference, or a non-utility theoretic approach such as replacement cost or avoided damage estimates. We group the remaining variables into the broad category of *context*$_{vars}$, which includes variables that describe both the user population and landscape in the vicinity of the primary valuation study site.

We include in the last category of context variables a ratio of local, surrounding wetlands to a local population count as an indicator of the availability of substitutes outside the study area relative to the local population. These two variables are measured in acres and a count of people, but are distinct from the acreage and population counts in the variable group, *study/site*$_{var}$. Other contextual variables include the average GDP per capita of the one or more states in close proximity to the study site and indicators of wetland type. An important feature of our meta-analysis model is the normalization we chose for the dependent variable. Our choice was motivated by our observation that most primary valuation studies use effectively obscure reasoning for choosing the population size for aggregating welfare measures and the boundaries and types of land included in the valuation study. This phenomenon is most evident in stated preference studies that sample from a particular region (e.g., a state) and ask participants about a particular, compartmentalized landscape. Studies such as these censor willingness to pay observations that are outside of that state and thus only estimate aggregate values conditional on the sampled population. These studies also compartmentalize the landscape by assuming that people's preferences or landscape structure and function can be meaningfully geographically isolated. By dividing the aggregate welfare measure by the count of the modeled population, we control for the arbitrary influence of censoring WTP of non-sampled populations that have positive WTP. We also control for the effect of the sampled population by including this count as an explanatory variable. Analogously, we normalize the aggregate welfare measures by the number of wetland acres valued in the study and include this acreage count as an explanatory variable.

A Parametric LWLS Regression with a Novel MA Dataset

The majority of the technical aspects of our discussion of the locally weighted least squares estimator are confined to the appendix. The purpose of this section is to lay out an intuitive understanding of how the parametric locally weighted least squares (PLWLS) approach works. The appendix describes a two-step process, the first is calibration where an unconventional type of parameter is estimated, and the second step is the use of the estimated parameter to develop weights for a weighted least squares regression.

The motivation behind developing the PLWLS estimator and going beyond OLS is that we wish to estimate a regression that is targeted towards each site (i.e., a site of interest or centered site) for which we desire an estimate of value. The motivation for selecting a potentially unique model for each site comes from a desire for forecast efficiency, or low prediction error variance. The basic concept behind the PLWLS regressor is that certain variables, referred to as *correspondence attributes*, are indicative of how *close* observations are to each other. Two observations that are *close* to each other provide more information about each other than two observations that are not. We make use of this correspondence information by applying lower weights to data that are less *close* to the policy site of interest. The idea of correspondence has arisen in a number of ecosystem service MA publications, but we are unaware of any attempts to formalize a systematic procedure for estimating or implementing correspondence.

An immediate challenge that arises in implementing this idea is that we do not know how to combine *correspondence attributes* with very different units. Thus we estimate parameters that serve as a normalization that allows us to combine dissimilar *correspondence attributes*. For example if we suspect that geographic distance between two sites and the difference between two sites in average income of the local population are both important indicators of correspondence, lacking a quantitative model, we have only our best judgment to guide us in deciding the relative importance of distance and difference in income. With PLWLS we are able to estimate parameters, referred to as *correspondence parameters* that allow us to add up the *correspondence distance* between two sites as measured by both geographic distance and the difference in income. An important challenge is that there is a cost to applying lower weights to certain observations, as we would be losing useful information if we incorrectly reduce the weight of a particular observation in the model for a policy site of interest. Accordingly, we allow *correspondence parameters* to equal zero (which results in the same OLS estimator in each regression) or any positive, real number. We also analyze the performance of the estimator in comparison to OLS in an artificial forecast simulation, described in the next section.

The main divergence of our model from a conventional OLS regression is that we have a regression for each observation; these regressions are distinguished by potentially unique weights used during estimation. Equation (3) contains the basic formula for estimating the weight applied to observation j in the regression tailored to site i. In this equation we have the sum of H terms in a negative exponential function.

$$\widetilde{\boldsymbol{\Omega}}_{i\,jj}^{-1} = e^{-\sum_{h=1}^{H} |a_{hi}-a_{hj}|\widetilde{\delta}_h} = e^{-(|a_{1i}-a_{1j}|\widetilde{\delta}_1+\cdots+|a_{Hi}-a_{Hj}|\widetilde{\delta}_H)} \tag{3}$$

The variable a_{hi} is a correspondence attribute where the subscript h indicates which attribute (e.g., income or geographic location) and the subscript i indicates the observation associated with the attribute.

Thus $|a_{hi} - a_{hj}|$ is an unweighted measure of correspondence distance, which is weighted by the estimated correspondence parameter, $\tilde{\delta}_h$, and the sum of these H terms is the argument of the negative exponential function. The resulting value, $\widetilde{\boldsymbol{\Omega}}_{i\,jj}^{-1}$, is the jth diagonal element of the diagonal, positive definite regression weight matrix, $\boldsymbol{\Omega}_i^{-1}$. The desired regression parameter vector, $\tilde{B}_i$, is calculated according to the WLS formula in equation (4), where the tilde above a variable indicates that we have estimated that variable via L-WLS.

$$\tilde{B}_i = (\boldsymbol{X}'\widetilde{\boldsymbol{\Omega}}_i^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'\widetilde{\boldsymbol{\Omega}}_i^{-1}Y \tag{4}$$

Here $\boldsymbol{X}$ is a $(n \times k)$ matrix of explanatory variables including an intercept term, Y is a column vector of observations of WTP of length n, and $\tilde{B}_i$ is an n-element column vector of parameter estimates. The subscript i indicates that the matrix $\widetilde{\boldsymbol{\Omega}}_i^{-1}$ has been estimated for observation i, which is the sole source of information that leads to a potentially unique parameter estimate for site i.

Jackknife Out of Sample Forecast Simulation

We implement a jackknife or leave-one-out forecast analysis in order to develop a better understanding of how our model might perform for actual forecasts for policy sites that have no corresponding valuation study. For the OLS model we drop an observation and estimate the regression coefficients without that observation, then using those coefficients we forecast the dependent variable and sample error for each observation. The forecast and sample error of the dropped observation is of particular interest since that observation is out of sample relative to the estimated parameters and coefficients. The jackknife provides n^2 forecasts that can be used to reconstruct an approximation of the sampling distribution. Because we lack equations for constructing standard errors that reflect variability in correspondence coefficients, the jackknife also provides a parallel means for assessing the PLWLS and OLS model variability.

The jackknife procedure for the PLWLS is very similar, but requires recalibration of the *correspondence coefficients* for each omitted observation. This procedure also provides us with a first approximation of the sampling variability of the *correspondence coefficients* themselves. A natural question is whether our PLWLS model outperforms OLS in the jackknife setting.

Data

Forecast Combination

To conduct the MABT dependent variable simulation, two basic steps are required. First, we must specify values for the explanatory variables pertinent to each wetland ecosystem and for each published MA model. Second we treat the estimated regression model from the original study as a stochastic predictive model with estimated coefficient means and variances which we use to simulate a distribution of the dependent variable. We use the National Wetlands Inventory geospatial database as the primary definition of wetlands while the NLCD 2006 dataset provides landscape data for the wetland type distribution in the Brander et al. (2006) meta-analysis. Refuge boundaries are taken from the USFWS Cadastral Special Interest layers (USFWS 2009); we specifically use parcels designated as "acquired" under the variable, "status".

Population density data are obtained from the SEDAC *Gridded Population of the World: Future Estimates* dataset for the year 2010 (CIESIN 2005). GDP data for the state(s) occupied by or immediately adjacent to each NWR are adjusted for inflation to the appropriate data year for each study using the BLS CPI Inflation calculator; these data are from the BEA's *SA04 State Income and Employment Summary* dataset (BEA 2012).

While many explanatory variables for MABT can be specified with little difficulty, geospatial and methodological variables require important assumptions. Because all three MAs estimate non-constant returns to scale, the geographic extent chosen for the analysis will impact the results. As we are interested in modeling wetlands in NWRs, we use NWR boundaries as the unit of analysis. Future work is needed to develop a formal procedure for endogenously identifying the appropriate unit of analysis for wetland ecosystem service modeling, especially in the context of non-constant returns to scale for wetland acreage.

Several alternative approaches for the treatment of methodological variables when predicting the dependent variable can be found in the MABT literature (Moeltner, Boyle, and Paterson 2007; Johnston and Thomassin 2010). In order to include passive use values in our BT estimates, we simulate a contingent valuation method for the two earlier meta-analyses that include methodological variables. We use model B from the Ghermandi et al. (2010) study, which omits methodological variables, as the study's authors indicate this is the best model among those estimated. Study quality variables for the Woodward and Wui (2001) meta-analysis were set to zero, implying that we are predicting the WTP estimates that would be obtained from a hypothetical, high-quality primary valuation study. Our approach to coding methodological explanatory variable for dependent variable prediction differs from existing approaches in the literature in that we view the results as a simulation of the results of a hypothetical

primary valuation study. This interpretation of the MABT model suggests that if we wish to estimate a hybrid of methods, we should not code binary dummy variables as fractions, but rather we could estimate results as if they were from multiple primary valuation studies and then average these results, perhaps using sample means for each methodological dummy variable as the weights in the average. We do not attempt to combine valuation results from multiple primary valuation methodologies in this paper. Rather we choose first the valuation approach (stated preference approach) most suitable for answering questions about the total value of ecosystem services, and we choose next the valuation method (contingent valuation method) most abundant in the MA datasets.

The data used to estimate flood control benefits from each MABT are given in Tables 2 - 5. The layout of the explanatory variable values matches Table 1. The variables for wetland type must sum to 1, so for example from Table 2 we can see that Arrowwood NWR is 99.8% fresh marsh (fresh marsh proportion obtained from NLCD 2006 gridcode 95 – emergent herbaceous wetland) and 0.2% woodland (woodland proportion obtained from NLCD 2006 gridcode 90 – forested wetland) . The population density variable in the Brander et al. (2006) meta-analysis is negative because the units employed are the natural log of 1000people/square kilometer and there are fewer than 1000 people in the average square kilometer in North Dakota. The many dummy variables that were coded to zero are omitted from these tables, but can be seen in Table 1. To predict the value of flood control, for example, the flood control dummy was set equal to 1 and all other service valued dummy variables were set equal to 0. The analogous coding is used to estimate the value of water quality provisioning.

A general review of the studies referenced in each MA publication indicates that some observations simultaneously valued more than one service provided by a single wetland site. Specifically, the methodological variables in Brander et al. (2006) and Ghermandi et al. (2010) are unlike conventional dummy variables, as they are not perfectly linearly related: for example, one valuation study may use multiple methods to obtain a result or a result may reflect the value of multiple services. Because no interaction effects among different services are estimated in any of the models, one resulting restriction is that the partial effect of predicting WTP for a single service provided by a wetland (e.g., flood control) is the same as adding that same service to another (e.g., adding flood control to a BT value that also predicts water quality provisioning value); this restriction can imply negative partial effects for certain services. For example, with the Brander et al. (2006) MA, valuing flood control alone will always return a positive WTP estimate, but simultaneously valuing flood control and water quality will have a positive but lower predicted value, indicating that water quality services have a negative effect. We handle this complication by always valuing only one service at a time. In the context of our interpretation of the dependent variable as a simulated study result, we simulate a primary valuation study estimated by a single methodology that focuses on a single service.

The Novel MA Dataset

While theory offers little formal guidance for the MA practitioner specifying the model to be estimated, existing MAs provide some guidance concerning functional form and relevant explanatory variables. Once the MA practitioner has assembled a list of explanatory variables to include in the model, obtaining the values of each variable for each observation is the next task. Challenges can potentially arise when attempting to find measurements of both the dependent variable and the explanatory variables. In the paragraphs below we describe examples of the process behind measuring the values of variables and how we address problems that arise. We follow with a discussion on the choice of variables included in the final model used for MABT. Some variables are included in the database that are not used in the final model; these variables may be useful for future modeling efforts.

Existing wetland ecosystem service MAs specify the dependent variable in terms of WTP per acre/hectare or WTP per person. To develop a model that follows the published literature, observations that are retained in our dataset must share a common normalization or units of the dependent variable – typically WTP per unit surface area or per person. Careful consideration and additional information is important when combining primary valuation results with different units and different welfare measures representing different services obtained from differing valuation approaches. The main assumption of the meta-analyst is that explanatory variables can be specified that control for these many sources of variation.

Following similar wetland ecosystem service valuation MA studies, we include a variety of economic valuation approaches as a component of our econometric identification strategy. By including multiple primary valuation approaches, we allow for a larger sample with more variation in explanatory variables. A number of studies were eliminated from consideration due to the author's reuse of a dataset associated with an earlier valuation study. Other criteria for eliminating a study from our model include uncertainty about whether the study focuses on ecosystem services attributable primarily to wetlands or if the study focuses on a broader landscape including uplands. An important final criterion that determines both sample size and model specification is the availability of values for all explanatory variables for all observations. A summary of the final data used in our MA regressions is provided in Table 6. Ultimately, the dataset we used for analysis contains 82 observations of WTP obtained from 26 primary valuation studies, and all studies are based on unique datasets. The first column of Table 6 contains variable names, with the dependent variable (2010 US dollars per 1000 acres per person per year) on the first row below the header. The second column is the sample mean of the 82 observations and the third column in the

table is the variance of the sample mean. All methodological variables are binary or dummy variables as is the variable, "coastal" for sites that are on the coast of an ocean.

The most frequently used approach for valuing wetland ecosystem services in our dataset is the stated preference approach. The Contingent Valuation Methodology provides 46 observations and the remaining 14 are from choice experiments. Both of the stated preference methodologies provide observations of WTP per person, typically as Hicksian Compensating Variation. Most of the remaining studies follow the revealed preference approach, all 15 of the revealed preference observations we use are based on the Travel Cost Methodology. We exclude valuation studies that implement the Hedonic Price Method because so few of these studies estimate the second stage regression necessary for converting implicit prices into a demand curve that can be used to estimate consumer surplus. The Hedonic Price Method also captures private market values that are fundamentally different from the public goods we are interested in, namely water quality and flood control.

The remaining observations retained in our final dataset are from studies that utilize economic valuation methodologies that are generally considered to be less theoretically appropriate. We lump together into a single omitted dummy variable studies that utilize damage avoidance and replacement cost (of capital). We include these studies in order to obtain a variety of observations for flood control and water quality provisioning services. In order to mitigate concerns that replacement cost studies of water quality overestimate value, we only use studies where the authors have identified that the Clean Water Act has led to mandatory water treatment.

Because some primary valuation studies simultaneously value more than one service, we utilize a variable called *joint* to allow for us to control for primary valuation studies that value multiple services at one time. For example, Roberts and Leitch (1997) report value estimates that include habitat, recreation, and aesthetics in a single stated preference study. For each instance such as this, we code each service variable to one and code the variable *joint* to be 3. While a more robust approach would be to include an interaction term for each combination of services, the approach we employ is useful because it does not consume excess degrees of freedom and also ensures that we can obtain reasonable identification with a model that already contains a large number of dummy or binary variables.

In primary valuation studies the measured WTP of a representative agent is often aggregated to the relevant user population, typically through multiplication (e.g., Bergstrom et al. 1990). More advanced approaches may segment the population by observable characteristics (e.g., Cooper and Loomis 1993; Bishop et al. 2000) or may include information to estimate distance decay (Sutherland and Walsh 1985). Distance decay is the intuitive concept that people further from a site will benefit less from the site than people who are closer. However, because not all studies contain estimates of aggregate WTP, this

process requires additional information from the MA practitioner. Similar problems arise with the Travel Cost Method which may report WTP normalized by person, trip, or household.

When additional information is required for estimating aggregate WTP associated with an observation, the MA practitioner typically must make a decision about how to proceed, potentially introducing error into the model. Some primary valuation studies may specify the geographic extent from which the sample was obtained, often delimited by political boundaries (e.g., Cooper and Loomis 1993; Phaneuf and Herriges 1999), but the study may not report relevant socio-economic data on the population of the area. For example, the local population count and average income are not reported in many valuation studies. For instances such as these, we use US Census historical data and BEA (2012) data to recover population and income information for counties and states associated with the user population.

One of the most important aspects of the data gathering process that may require supplementary information beyond the primary valuation study is the identification of the geographic extent of the wetland that is valued. Most existing wetland MAs include a surface area regressor, allowing for non-constant returns to wetland area, this implies that both aggregate values and values-per-acre may be misestimated if wetland extent is measured with error. Identifying the extent of the wetland valued in an observation in the dataset also allows for more complex geospatial analysis of the site's geographic context. Thus we imposed the requirement that the study must provide sufficient information to identify the geographic extent of the studied wetland. We also eliminated from our model studies that provide a value for extremely large wetland extents, such as the entire country (e.g., Bergstrom and Cordell 1991).

The additional analysis and decisions that the MA practitioner needs to make in order to estimate the extent of valued wetlands can be usefully illustrated by example. In Breaux, Farber, and Day (1995) a wastewater treatment wetland in Thibodaux, LA is identified but with too little information in the publication to identify the site on a map. By searching the Internet for documents relating to the "State Department of Environmental Quality", "Thibodaux, Louisiana", and terms relating to wastewater treatment and discharge, we found a document describing the site. The site in Twilley and Boustany's (1990) report matches closely the description in Breaux, Farber, and Day (1995), including the extent of treatment wetlands (230 hectares vs. 570 acres, respectively) and both describe a two ridge system with a drainage canal. Additionally, both reports cite locally relevant studies by William H. Conner and John W. Day; other similar documents confirming the site were also found. The additional information obtained in the Twilley and Boustany (1990) document allowed us to find the site in the EPA's Water Quality Assessment Status reports (http://watersgeo.epa.gov/mwm/?layer=305B&feature=LA120207_00 &extraLayers=null), providing sufficient information for identifying the boundaries of the site in ArcGis. We then construct a polygon matching the boundaries of the site, allowing for analysis of the surrounding population and geography.

While the Breaux et al. (1995) study valued a small geographically specific wetland, Bergstrom, Stoll, Titre, and Wright (1990) value a substantially larger wetland system, estimated at 3.25 million acres by the authors. Using their figure 3, a map of the counties in the study region, we identify the appropriate Louisiana counties in ArcGis. Because Bergstrom et al. (1990) attribute all consumer surpluses in their study to wetlands in the selected counties, we retain all wetlands therein as the scope of valuation. The procedure for identifying coastal wetlands valued in Costanza, Farber, and Maxwell (1989) was similar. In their study a section includes estimates of the value of hurricane protection services provided by Terrebonne Parish coastal wetlands. We define their site first by selecting wetlands in Terrebonne Parish and then selecting by hand the subset of these wetlands that are between populated areas and the Gulf of Mexico.

Ultimately, the question of how big the wetland study site associated with a primary valuation study is can potentially have an unclear answer. Stated preference studies evaluate willingness to pay to protect or prevent the loss of a precisely defined wetland area (i.e., indicated on a map or with a precise description) (e.g., Sutherland and Walsh 1985; Sanders, Walsh, and McKean 1991), of a generic and locally relevant wetland (e.g., Johnson and Linder 1986; Blomquist and Whitehead 1998; Bauer, Cyr, and Swallow 2004), or of a certain portion of a larger nearby wetland area(e.g., Beran 1995; Bishop et al. 2000; Whitehead et al. 2009; Petrolia and Kim 2011). Even for sites that value wetlands of a well-defined extent, the wetland ecosystem around or nearby the site may be substantially larger. Attributing the average per-acre willingness to pay for a smaller subset of wetland acres to all adjacent wetland acres may lead to a large upward bias in the aggregate welfare measure. Accordingly, when applicable, we specify the wetland surface area variable as the value (i.e. the stated number of acres valued) discussed in the primary valuation survey. As we discuss below, the accounting of substitute wetlands in a radius around the study site as an explanatory variable allows for us to control for changes in WTP that are related to the broader wetland landscape.

Beyond estimating the size of the wetlands being valued, a further conceptual issue arises when identifying wetland acreage from a primary valuation study. This occurs when the study values a hypothetical or generic rather than an actual wetland. Johnston et al. (2002) and Bauer et al. (2004) are examples of valuation studies where a hypothetical or generic site is valued. Both of these studies, however, indicate a context that motivated the research; we use this context as the actual site of valuation in order to be able to obtain information about the geographic context of the wetland.

The relatively recent wetland MAs of Brander et al. (2006) and Ghermandi et al. (2010) include dummy variables distinguishing wetland type. We follow this approach, but we use continuous variables representing the proportion of wetlands at the site in each subsystem, as defined by Cowardin et al. (1979). Because many wetland valuation studies consider wetlands that include a variety of wetland

subsystems, this flexible approach can capture more variation in sites and is less prone to measurement error at the expense of requiring more geospatial analysis. However, because we are using other spatial variables, there is little difficulty in measuring the wetland subsystem proportions beyond identifying the boundaries of each site. Ultimately through pre-testing, we eliminate all wetland classification variables from our regression models; these variables may prove useful in future analyses.

With a well-defined digital map of each wetland, we can assess more complex geospatial variables and relationships. In order to control for the availability of substitute wetland sites, we follow Ghermandi et al. (2010) who include a variable for the total area of wetlands in a 50km radius around the center of each site. However, valuation studies that value geographically extensive wetlands, such as all the wetlands in a particular state, are likely to be associated with a wider scope for substitution than studies that value small wetlands. Because of this concern we pursue a more flexible method for measuring substitutes that varies with wetland surface area. In our model the radius begins at the outer boundary of the study site (rather than the center of the site) and extends for the number of miles that equals the cube root of study acres. Thus the wetland substitutes variable for an 8000 acre site would include all wetland acreage in a 20 mile radius (as the cube root of 8000 is 20) beyond the boundaries of the site. This functional form was chosen based on our best judgment, and in part due to its positive first derivative and negative second derivative, which causes the radius to increase with a study's wetland acreage but at a decreasing rate. We use the NLCD dataset that is closest in time to the year of data acquisition to define local substitute wetlands. An important limitation in how we account for substitute sites is that we do not distinguish among different wetland types. For example, a wetland study site that consists only of brackish wetlands for which freshwater wetlands may be a poor substitute has included in the count of substitutes both freshwater wetlands and brackish wetlands.

We use NASA-SEDAC's Gridded Population of the World v3 dataset (http://sedac.ciesin.columbia.edu/data/collection/gpw-v3) to count the population around a wetland site in the same manner as we count substitute wetlands. We include this variable in order to control for variations in demand for wetland services associated with each site. We included this variable as a measure of the study and site context, as the local population variable differs from the population over which a benefit estimate is aggregated. Ultimately, the wetland substitute and local population measures are used as a ratio variable in our regression equation. The intuition behind this specification is that the ratio of local people to local wetlands might be indicative of the degree of scarcity of wetlands and associated ecosystem services.

For the PLWLS estimator, we also include latitude and longitude measured in meters from a common point in the western hemisphere in the Albers 1983 projection, obtained from analysis in ArcGis 10. Distance is measured in the Euclidean sense; we use the familiar Pythagorean distance formula to

calculate the distance between all observations in the sample. This value is used only as a correspondence attribute, as we are unaware of any straightforward means of accounting for distance between observations in an OLS regression.

Explanatory Variable Values for Forecasting

The application of our MA models for out-of-sample forecasts of NWR ecosystem service benefits requires little additional data. We use USFWS Cadastral Special Interest Layer polygons with a status of 'acquired' as our definition of the extent of each NWR. These polygons combined with NLCD 2006 land cover data provide us with a means to estimate the surface area of wetlands in each refuge, which is used to construct the remaining geospatial variables. The population variable that is a study/site variable (a distinct measure from the local population variable that describes the geographic context of the site) is set as the mean of study populations in our dataset. We choose this value for simplicity, though the actual application of results to a policy question would benefit from a more carefully and specifically defined population count.

Results

Forecast combination

The results of our Monte Carlo simulation of WTP per acre can be found in Tables 7 to 12. Tables 7 to 10 contain estimated quantiles of WTP based on the one million multivariate random normal parameter draws in our Monte Carlo analysis; each table contains a summary of the simulated distribution of WTP for flood control and water quality at a refuge. The results for flood control are in the top half and the results for water quality provisioning are in the bottom half of these tables. Each row of Tables 7 to 10 contains an estimate of WTP per year per acre from a particular meta-analysis regression model. The last two rows within each service are the precision-weighted and evenly-weighted averages of the three estimates above. We can see that med(WTP) appears to converge to $e^{E[X\beta]}$. This is a basic feature of the lognormal distribution based on a symmetric normal distribution. Tables 11 and 12, respectively, contain the results of our mean and variance estimates for flood control and water quality. The first numerical column is our estimate of the mean of the dependent variable after being exponentiated by the antilogarithm. The second column of numerical data is the simulated variance of the mean ,and each row contains one of the NWRs evaluated by one of the meta-regressions. A comparison of the dispersion of WTP estimates from each meta-analysis, indicated clearly both by the variance estimates and the 5th and

95th estimated percentiles, suggests that the Ghermandi et al. (2010) meta-analysis is far more precisely estimated than the two older meta-analyses. While this conclusion might be a result of estimation error due to our assumption that all sample covariances among parameters were equal to zero, with limited information the Ghermandi et al. (2010) meta-analysis appears to be the most precise by a substantial margin. Accordingly, we suggest that the Ghermandi et al. (2010) MA values are the best estimates that can be obtained from existing MA models and can be used in place of the forecast combination results for simplicity.

The point estimates in Tables 11 and 12 are most similar between the Brander et al. (2006) and Ghermandi et al. (2010) models, while the Woodward and Wui (2001) values are substantially larger. This divergence can be attributed in part to the inclusion in the Woodward and Wui (2001) meta-analysis of study quality variables, which indicate that lower quality studies systematically produce lower welfare estimates; as we coded the variables for a high quality study, the estimates are larger than the average study. Figure 1 is a bar graph containing point estimates of WTP per acre per year for each service at each refuge and estimated with each MA model. In Figure 1, the left hand axis corresponds to the blue bars for the Woodward and Wui (2001) point estimates while the right hand axis corresponds to the green and red bars for the Ghermandi et al. (2010) and Brander et al. (2006) studies. An important feature of the welfare estimates concerns the differences across MA models in the relative WTP estimates for each refuge. While both the Brander MA and the Ghermandi MA place Blackwater as having the most valuable wetlands, The Woodward MA places Blackwater NWR as third most valuable per unit of land. This result appears to be due largely to the inclusion of socio-economic variables in the later two MA models.

Next we aggregate WTP estimates over all wetland acres in each refuge for each service. Figures 2 and 3 are graphic representations of our estimates of WTP for ecosystem services supported by all NWI identified wetlands in each refuge. The corresponding numerical values can be found in Table 13 along with median (obtained via point estimate) WTP and the total count of NWI identified wetlands within each refuge. As discussed above, by our judgment, the best estimates of WTP are those obtained from the point estimate method of obtaining the median from the Ghermandi et al. (2010) meta-analysis WTP distribution, found in the last 8 rows of Table 13. In this case our choice of best is motivated entirely by the simulated variance of the mean of each forecast. The simulated variances indicate that the Ghermandi et al. (2010) study produces the most precise estimates and that simulated means are unreliable due to the assumptions required for estimation.

The results in Table 13 and Figures 1, 2, and 3 generally indicate that for wetland ecosystem services the Okefenokee NWR is most valuable as a whole with the Blackwater NWR providing moderately less valuable ecosystem services. The large estimated value of the Okefenokee NWR is largely due to the extensive wetland surface area, as median values per acre are among the lowest of the

four refuges considered across all three MAs. The aggregate values of Arrowwood NWR and Sevilleta & Bosque del Apache NWR wetland ecosystem services are substantially lower, by a factor of approximately ten. The primary reason for these lower values is the limited surface area of wetlands in these two refuges. The values of the average acre of the vast Okefenokee NWR are lowest primarily due to the decreasing returns to scale relationship estimated in all three MAs. The high values per average acre of Blackwater NWR wetlands are due largely to the high incomes and population densities coupled with the refuge's modest surface area. Generally we find that the results of the MABT with existing MA studies are in line with our imprecise, qualitative expectations.

OLS

The results of our OLS regression can be found below in Table 14. We report Huber-White or heteroskedasticity robust standard errors, t-statistics, and the p-values associated with the t-statistic for each parameter. The parameters estimated for both water quality and flood control are significant at the 10% level or better. The water quality parameter is significant at the 5% level; the flood control parameter just barely misses that mark, suggesting that the parameter estimates are reasonably precise. The parameter estimate for the number of acres valued is negative and significant at better than the 10% level with robust standard errors. The parameter for population is similar in magnitude to the parameter for acres, but the p-value is less than 1%. Because the dependent variable is normalized by acres and population, the interpretation is that a 1% increase in one of these variables leads to about a 0.5% decrease in WTP/acre/person, which suggests diminishing returns to expanding the scope of acres valued or the scope of the population for aggregation. The variable, joint, which indicates how many services were jointly valued is strongly significant and indicates that adding additional services to a valuation study results in a reduction of the estimated value relative to a model where the additional services were valued separately. The results of our OLS forecasts are discussed with the results of the PLWLS estimator in the next sub-section as well as in the discussion section.

PLWLS

As the calibration of *correspondence parameters* is the first step in the PLWLS estimator, we present these values first. The results of our PLWLS calibration can be found in Table 15. All *correspondence attributes* were standardized by their sample means and variances prior to calibration, with the exception of Euclidean distance which was converted from meters to 1000's of kilometers. In Table 15 we have removed the transformation for correspondence attributes other than distance to

facilitate a comparison. The results of the calibration step indicate that GDP and Euclidean distance between sites are important non-methodological determinants of correspondence among studies in our sample. Additionally, studies that value similar services and which aggregate over a similar population have higher correspondence with each other than otherwise. The PLWLS calibration step found that the number of acres valued by a study was not a determinant of correspondence, a notable result that might be reassessed in future studies. The moderate values for these parameters and the moderate weights (typically between 0.01 and 0 .9) that are consequently applied in each regression suggest that the algorithm is moderately down-weighting observations with poor correspondence, but retaining ample information for reasonably robust estimation.

The next step in the PLWLS procedure after identifying correspondence parameters is to use those parameters to calculate a $(n \times n)$ matrix of regression weights for each out-of-sample study/site of interest. These regression weights are used to calculate a regression for each site and also can be used to rank observations according to their relative information content. For any given centered site, observations that are weighted more heavily are assumed to have greater correspondence and therefore be more informative about the centered site.

We provide several graphs that illustrate correspondence in 2 dimensions; we specifically depict the NWR study sites as the centered observation in each graph in Figure 4. Figure 4 contains a plot for each refuge, where each refuge is the centered site indicated by the open circle towards the top-right of each graph, which is also the graph's origin. In each graph the horizontal axis represents the weighted difference between each data point and the centered observation Filled circles that are colored blue receive lower weights, while magenta circles receive higher weights, indicating greater correspondence. The four smaller filled circles represent the four case study NWRs, which can be seen to all have the same population, but varying incomes. The purpose of the figure is to demonstrate that the correspondence parameters give rise to weights that display a similar pattern across these out-of-sample observations or policy sites.

While the OLS regression treats each observation equally, the PLWLS approach allows us to rank observations according to the weight applied in each centered regression. The highest ranked observations contribute the most information, so the forecasted primary valuation study results are associated most strongly with the characteristics of the most highly weighted observations. Tables 16-23 contain the ten observations in each centered regression receiving the highest weights for each of the 4 case study refuges for both water quality and flood control services. The first four tables are for water quality and the next four are for flood control and storm surge protection. The top row of each table contains the values for the centered NWR followed in the second row by the column headings. GDP per capita values are all in 2010 US dollars. Euclidean distances are in kilometers. The regression weights are normalized so that all n=82

observations have weights that sum to 82; this normalization facilitates a simple comparison with OLS weights that are always 1 by assumption. Some rows in these tables appear to be duplicates, which is a result of variations in site attributes not included in the table such as the number of acres of wetlands valued. For example, in Table 16 the first 3 observations are from Bishop et al. (2000), which differ in both the measured value of WTP/person/acre/year and the number of wetland acres valued, which are both variables not included in these tables.

Generally, one can see that studies that value the same service are always the highest ranked observations for all 8 examples. High correspondence observations that value the same service as the centered observation tend to have markedly higher weights than subsequent observations that value other services; however this is not always the case. In Table 20, for example, the weight applied to the Costanza et al. (1989) flood/storm surge damage avoidance study is substantially lower than the weights applied to the higher correspondence flood control studies, which is consistent with the non-zero *correspondence parameters* estimated for GDP per capita and Euclidean distance. Both of these variables differ considerably more between Arrowwood NWR and Costanza et al.'s (1989) Louisiana study site and the higher ranked prairie pothole observations, as can be seen in the table.

We present the valuation forecasts of a stated preference study of flood control and water quality benefits for each of our NWR policy sites in Tables 24 and 25. The former table contains the median and mean of the dependent variable after reversing the log transformation and the values are scaled to 2010 US dollars per thousand acres per thousand people. The latter table contains median and mean aggregate values where the population is specified as the mean value in our dataset, about 3.5 million people. The median population is about half as large; the mean population in our dataset is relatively high due to several observations that aggregate benefits over large populations. The median WTP values are the point estimates of WTP forecasted by OLS and PLWLS estimators. For each estimator we include a forecast of both the median and mean values of willingness to pay. The magnitude of the difference between the median and the mean is inversely proportional to the precision of each model, and the consistently smaller gap between mean and median for the PLWLS model implies that this model is consistently more precise than the OLS model. We also provide acreage counts used during estimation and aggregation in Table 25. Also of note, many of the PLWLS dependent variable estimates, both mean and median, fall between the mean and median of the OLS estimates, implying that the PLWLS results do not suffer from extensive bias relative to the results from the unbiased OLS estimator. We highlight the mean value single service revealed preference study results as we consider these to be the best estimates (i.e., for forecasting the value of ecosystem services when estimated by a primary valuation study) available from our MA regression methodology. Under our suggested interpretation of the forecasts of the dependent variable,

best estimates include the judgment that a stated preference study of a population with about 3.5 million people would be the best choice to estimate the total economic value of each service.

Jackknife Leave-One-Out Analysis

The results of our jackknife leave-one-out procedure indicate that the additional information used in the PLWLS forecast may be useful for lowering out-of-sample forecast variances. We found that of 82 observations, the PLWLS algorithm when forecasting an out-of-sample observation produced a lower variance estimate than OLS 50 times (61%). The leave-one-out forecasts of the PLWLS estimator beat the full data forecasts of OLS 35 out of 82 times (43%), while the leave-one-out forecasts of the OLS estimator only beat the full information version of the PLWLS estimator 18 out of 82 times (22%). Future work may focus on identifying patterns that could be useful for predicting whether OLS or PLWLS is more likely to produce a more efficient out-of-sample forecast.

Discussion

We have combined the values obtained from MABT using 4 wetland meta-analysis datasets in Tables 26 and 27, which contains results for flood control and water quality provisioning, respectively. Tables 26 and 27 contain forecasted ecosystem service valuation results from simulated stated preference studies for each refuge and for the 5 MA models (the last two models are based on our dataset). These tables include a row of results that are the median value or point estimate. Additionally, the mean values are included below each row of median values. As mentioned above, an important aspect of evaluating each model is the magnitude of the model's error variance. The larger a model's error variance is, the larger the divide between the median and mean value will be. The PLWLS model has the smallest gap between median and mean estimates of WTP, implying that the PLWLS model is the most precise.

The high precision of the PLWLS estimator comes at the expense of introducing variability through the estimated correspondence parameters; this increased variability is not captured by conventional, robust standard errors. However, the alternative *ad hoc* process of choosing a sample that is thought to have high correspondence with the policy site also introduces variability that is not accounted for when estimating standard errors. Accordingly with the PLWLS and all other econometric models, it is important to keep in mind that all results are conditional on the sample and model specification, and in the case of reported standard errors estimated for the PLWLS regression parameters the values are conditional on the estimated correspondence coefficients which effectively serve as a means for resampling the data.

For the flood control benefit forecasts using the PLWLS methodology, the top observations (Tables 20-23) are values from primary studies that use a damage avoidance approach to quantifying flood control benefits. Pre-testing with a variety of combinations of correspondence attributes indicated that valuation approach (e.g., stated preference, revealed preference, damage avoidance, or replacement cost) was generally not a determinant of correspondence for our dataset. Accordingly, forecasting a stated preference valuation result with a substantial proportion of the information coming from damage avoidance studies is more appropriate than using a stated preference study that values a different service. The result that flood control damage avoidance studies and flood control stated preference studies do not differ in correspondence can also be interpreted as being indicative of low WTP for the passive use value of flood protection services; in other words, people are unwilling to pay more than the costs of avoided damages for flood protection services.

All MABT results in this paper can be interpreted as coming from a stated preference study, with the exception of the estimates obtained from the MA model of Ghermandi et al. 2010, which lacks controls for study methodology[1]. While we present these 5 models together in Tables 26 and 27, it is important to caution that for the existing MA studies only the results of the median calculations have been made with all necessary information. Another important difference lies in our inclusion of the population over which benefits are aggregated as a dependent variable. The additional assumptions (that the standard errors of estimated parameters have zero covariance) required to calculate the mean value of the dependent variable for the MAs other than our own potentially leads to small-sample inaccuracies. Not without surprise, we find that the accuracy of mean values obtained from the Monte Carlo assessment of published MAs is questionable, especially considering how tremendously large some of these estimates are. Ultimately, we conclude that too much information is lacking to perform adequate benefit transfer with the information provided in the publication of each published MA study when mean values are of interest.

We also provide a graphic comparison of the median values obtained from each of the 5 MA models in Figures 5 and 6, and in these figures we compare the results for the average acre of wetlands. Both figures have a vertical axis that has been logarithmically transformed to allow us to fit all 5 models in a single, compact figure. The graphic presentation of the results from all 5 MA models indicates what we believe is the most reliable strength of using MA models for evaluating ecosystem service values; that

[1] This is one reason why the Brander et al. (2006) study was used in the Phase 1a report rather than the more recent Ghermandi et al. (2010) study as including a precisely estimated (significant) study methodology variable (for the contingent valuation methodology) allows for more confidence in controlling for welfare measure consistency.

is, MA models appear to be most valid for ranking sites in terms of the relative value of ecosystem services. For example, in Figure 5 we can see that all but the Woodward and Wui (2001) results indicate that the average acre of Blackwater NWR supports the greatest (by a substantial margin) value of flood control services. The same 4 MA models also indicate that the average acre at Arrowwood NWR or Okefenokee NWR consistently provides flood control services of lower value than the other refuges.

Figure 6 provides a less consistent ranking, relative to the flood control rankings, of water quality related ecosystem service values among the 4 case study sites. For water quality related ecosystem services, the wetlands of the Sevilleta and Bosque del Apache are consistently ranked as among the most valuable and the wetlands of the Okefenokee NWR among the least valuable. However, the relative ranking of the wetlands of Arrowwood NWR and Blackwater NWR for providing water quality related services are less consistent across MA models. For both of these figures, it is important to note that for all models except the PLWLS model the relative ranking across refuges within a model (e.g., in the Brander et al. (2006) model) cannot change between the two services, a restriction of the single equation OLS approach when interaction terms are not included.

In comparison to the median per acre values from the Brander et al. (2006) meta-analysis, the dataset we have compiled indicates dramatically higher median estimates of ecosystem service flows. At the same time, using the best available data, the mean values obtained from the PLWLS estimator are generally smaller. Due to the problems with estimating the mean of the dependent variable using the Brander et al. (2006) model and due to the problematic exclusion of population as an explanatory variable, we believe the results from our dataset are more conceptually appropriate for MABT. Additionally, due to the exclusion of non-domestic studies from our dataset and due to the use of the PLWLS estimator, we expect to have greater correspondence and therefore reduced transfer error with our model and dataset.

The mean of our PLWLS estimator is what we consider to be our best forecast, conditional on the population count used during estimation. An important contribution of our paper is the modeling and associated acknowledgement that the population over which welfare estimates are aggregated in primary valuation studies is essentially always a choice of the original analyst and dictated neither by the model chosen by the analyst nor the context of the site associated with the ecosystem services being valued. Studies that utilize an empirical approach to restricting the population over which benefits are aggregated are surprisingly rare; Sutherland and Walsh's (1985) study is the only domestic exception we encountered in our literature search. Clearly an important next step is to develop a more formal empirical means for choosing the population over which benefits are aggregated.

Essentially, we follow the existing MA literature in agreeing that methodological covariates can be difficult to assign for forecasting ecosystem service values when one is simply interested in knowing

how an acre of wetlands impacts the welfare of society. We expect that the estimation of a single number that is free of methodological underpinnings is not the goal of MABT, not anytime soon. Rather, we reiterate the argument that the best interpretation of the dependent variable obtained from a MA regression model is a simulated primary valuation study result. As ecosystem service valuation studies are typically conducted in the context of answering a research or policy question, one must choose a specific valuation methodology to simulate a primary valuation study. If interest lies in a value that is an average of results obtained from a variety of methodologies, we recommend simulating each valuation methodology by coding methodological dummy variables to 1 or 0 and then taking the average (perhaps with unequal weights) of the final forecasts. We specifically caution against coding dummy variables for binary concepts as fractions (e.g., coding them at their sample means); if this caution is not followed, the resulting forecasts will be non-linear functions of multiple valuation methodologies that have no clear interpretation and no clear means for empirical validation.

The results of the regressions using our dataset produce numbers with a magnitude most comparable to the values estimated by Woodward and Wui (2001). In comparison to the valuation forecast results obtained from the median of the Ghermandi et al. (2010) MA model, our OLS values tend to be about 50 times higher. The mean values simulated for the Ghermandi et al. (2010) study are substantially closer to the PLWLS mean values obtained with our dataset, though substantial differences exist. Because we do not have access to information regarding even the average population in the datasets associated with the 3 previously published MAs, we cannot confidently say that the majority of the variation in benefits is not due to a difference in the population of beneficiaries that was used to make the forecast.

Conclusions

The process of learning about the behavior of the Locally Weighted Least Squares estimator in our sample has led us to conclude that the most telling way to understand the estimator is in the context of penalties. Starting from an OLS regression where no observation is penalized, when we consider a local regression for site i, observations that are distant (in terms of correspondence) from the central observation are penalized. The weights are unity less the penalties determined by the parameterized exponential equation described in the appendix. The process of calibration works by fitting a parametric variance equation to sample variances and efficient forecasts are made based on patterns identified in the calibration process. The results of our PLWLS estimator seem promising, yet the impact of clustered observations and a small sample size on the performance of the model along with a reliable means for estimating regression coefficient variability due to resampling are still important unanswered questions.

The appropriate use of welfare measures is dictated by the questions one wishes to answer. The relative lack of attention to the difference between mean and median values of the dependent variable (e.g., Woodward and Wui 2001; Brander, Florax, and Vermaat 2006; Ghermandi et al. 2010; Brander, Brouwer, and Wagtendonk 2013) is problematic as these two measures of central tendency are appropriate for answering different questions. Median values may be useful for predicting the outcome of a vote for which an outcome requires a simple majority. Benefit-cost analysis and in general estimation of economic benefits on the other hand typically require that one uses the value of the mean of the dependent variable. For models estimated with the dependent variable in log form, estimation of the median value of the dependent variable is easy, but this ease comes at the cost of potentially using the wrong value (biased downwards) which for benefit-cost analysis will systematically lead to biased decisions that lead to a reduction in social welfare as measured by aggregate benefits due to inadequate protection and restoration of wetlands that provide important services.

We are ultimately interested in structural methods of modeling the contributions of wetland ecosystem services to human welfare, and the literature as of yet contains only models that are essentially reduced form in nature. We use the term *structural* in the sense that estimated parameters can be interpreted as causal and in contrast to a reduced form model where causal claims are potentially wrong due to endogeneity. Smith and Pattanayak (2002) use the term differently, to refer to the origins of the benefit transfer model in microeconomic theory, which Bergstrom and Taylor (2006) refer to as a *strong structural utility theoretic*. Our interpretation of the dependent variable as a valuation study result calls into question the desire to have a strong structural utility theoretic model derived from an individual consumer's assumed utility function. The reason for this divergence is that estimates of a change in welfare potentially have a very different data generating process with different sources of variability relative to the underlying changes in welfare that researchers are trying to measure.

Our model is another reduced form model because endogeneity may be present, but by clarifying the interpretation of the dependent variable and also identifying the population and acreage associated with a welfare estimate as choices made by the original investigators, we believe that our model has features closer to a structural model than earlier attempts. Additionally, because we are primarily interested in using our model for forecasting, efficient forecasts may be more important than the causal interpretations afforded by structural models. Also relevant to the notion of a structural model is the question of whether we are forecasting the results of primary valuation studies or directly forecasting ecosystem service values. The former interpretation, which we recommend, also suggests a different meaning of causal impacts; the interpretation of a causal partial effect indicated by a regression parameter is with respect to the results of a primary valuation study. Ultimately, divorcing estimates of WTP from the methodology that uncovers them is more likely to obscure the nature of ecosystem service value

estimates than to provide clarity through a reduction in the contextual details that come along with value estimates. Concerns that a MABT model can be manipulated to achieve any particular result via changing methodological explanatory variables can be assessed by examining the appropriateness of the methodologies coded during MABT for answering the question the values are intended for. Our interest in the total value of services suggests that stated preference methodologies are the only relevant methodology to use for forecasting.

Future work will likely increase the efficiency of benefit transfers. Efforts to increase efficiency can focus on expanding the MA dataset through several avenues: inclusion of non-domestic studies and appropriate controls, increasing the sample size by adding additional services to the analysis, and increasing the sample size by more carefully reviewing existing studies and relevant technical reports for missing information that prohibited their use in the current analysis. Validation and updating of the model through future primary valuation studies is also an important aspect of increasing the efficiency of MABT. Work is ongoing to identify common domestic wetland sites that have poor correspondence with the existing MA dataset, as primary valuation studies of these sites are likely to greatly enhance our ability to produce efficient forecasts. Increasing the efficiency of MABT models for wetland sites that are both common and understudied is a particularly promising avenue for future primary valuation studies. The development of useful applications of MABT models to management decisions may be illustrated with a comparison of potential refuge acquisitions by comparing a ranked list of real-estate costs with a ranked list of forecasted welfare changes. Rankings such as these may be useful for finding refuge acquisitions that are likely to have the greatest benefit to cost ratios.

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Appendix: A Parametric Locally Weighted Least Squares Regression Procedure

The PLWLS Model Foundation

Our PLWLS methodology has at its core a GLS-like approach to efficient estimation of regression coefficients. The GLS method is widely known to produce an estimate of regression parameters that is more efficient than the conventional OLS estimator when the correct weight matrix is used (Hayashi 2000, 137). In order to estimate GLS, we require knowledge of the appropriate efficient weight matrix to use during estimation, which is usually a diagonal matrix where each element is the respective observation's known inverse error variance. Typically, however the appropriate weight matrix is not known and must be estimated. The purpose of the estimator developed below is a new approach to the estimation of the appropriate weight matrix for any benefit transfer of interest. The process detailed below broadly consists of an initial calibration stage that estimates the parameters that are used in a function for estimating the variance of each observation in a sample that is tailored to a specific observation, followed by a suite of GLS regressions that utilize the estimated parameters from the calibration stage.

Because we are developing a model based on the correspondence among observations, it is important to fix the basic idea of our approach before exploring the detailed steps necessary for estimation. Ultimately, we are interested in estimating an efficient regression for each site in our sample. Consider a site, i, that is the subject of a meta-analysis benefit transfer. The ultimate objective of the approach we develop is an efficient estimator of B_i which is intended to be used for forecasting benefits for site i. Consider the following meta-regression equation for site i.

$$y_j = \mathrm{x_j} B_i + e_{ij} \tag{5}$$

where y_j is a scalar, measured (by a primary valuation study) value or WTP per acre per person, $\mathrm{x_j}$ is a row-vector of k explanatory variables for site j, B_i is the k element population parameter column-vector for site i, and e_{ij} is a scalar, zero mean stochastic population error term associated with the data $\mathrm{x_j}$ and y_j and the parameter vector, B_i. Following the classical regression approach, we wish to estimate the value of B_i that minimizes the sum of squared errors across the sample of n predictions of the dependent variable, y. B_i is indexed by i to indicate that this parameter is optimized to efficiently forecast the dependent variable for a particular site, i. Estimates of the population parameter, B_i, are represented in the following equation as $\tilde{B}_i$.

$$\tilde{y}_j = x_j \tilde{B}_i + \tilde{e}_{ij} \quad (6)$$

A tilde over a variable indicates that the variable has been estimated by a regression or similar model. We are interested in efficient estimates of B_i, that is where we expect e_{ij}^2 to be as low as feasible for the available data. Generally, we are interested in cases where $i = j$, indicating that the particular choice of B is intended for the data at hand, while cases where $i \neq j$ are typically not of interest.

The most straightforward and familiar estimator of $B_i$for data y_i and x_i is the OLS estimator, $\hat{B}_i$,

$$\hat{B}_i = (\boldsymbol{X}'_{(i)}\boldsymbol{X}_{(i)})^{-1}\boldsymbol{X}'_{(i)}Y_{(i)} \quad (7)$$

$\boldsymbol{X}_{(i)}$ is a $(n_i \times k_i)$ matrix contains n_i rows of the k_i element data row-vectors x_j. Analogously, $Y_{(i)}$ is a $(n_i \times 1)$ matrix (column vector) of scalar values of y_j. The subscript, j may take on values from 1 to n_i. The subscript, (i), indicates that a particular data matrix is intended for calculating $\hat{y}_i$, that is an estimate of the originally measured value of y_i. The typical procedure is to choose or weight by some means the rows of $\boldsymbol{X}_{(i)}$ and $Y_{(i)}$ such that the estimate of Y_i is efficient relative to the available information. The fundamental intuition behind a weighted regression is that certain observations contain less information about the underlying population from which the sample was drawn, and by correctly reducing the weight of those less informative observations, we are preserve the relative information content across all observations. In contrast, if we knew the appropriate weights but we did not use them, the more informative observations would be effectively downweighted relative to the information they contain about the population.

It is important to distinguish an efficient estimate of B from the particular B_i that is an efficient estimator of Y_i. That is to say we are not necessarily interested in the estimate of B that is most efficient on average for all observations, but rather for any given observation we are interested in the parameter that is *a priori* expected to be most efficient for that observation or a set of observations that share something in common, such as their vicinity. The distinction between the two reasons for choosing estimators is most apparent when data are systematically eliminated from consideration for a particular site i by removing said data from the data matrices used to estimate B_i. The motivation for eliminating an observation is typically that the analyst thinks that observation is relatively uninformative about the site of interest due, for example, to an analyst's qualitative expectations of poor study/site correspondence.

In order to quantify the idea of study and site correspondence, we assume that an observation's membership in the sub-population centered on site i is a function of observable variables, a, referred to throughout as *correspondence attributes*. Specifically, when considering the membership of an observation, j, in the population centered about site i, we are interested in the measure, $g(a_i, a_j; \delta)$, where $g(.)$ denotes a weighting function and δ is a *correspondence parameter* that we will estimate.

At least two statistical interpretations are available to motivate this procedure. First and foremost, to pair the above assumptions with the efficient GLS estimator, we can assume that the error variance for observation j in the population centered on observation i is consistently approximated by the function, $g(a_i, a_j)$. Second we can alternatively interpret the elements of $g(a_i, a_j)$ as probability weights that adjust each observation's weight to be consistent with a sampling frequency such that it is as if the observation were sampled from the sub-population centered on site i. This latter interpretation is analogous to using weighted least squares to correct a stratified sample. Sites that are closer to the center of the population centered at site i are more likely to be sampled when sampling is focused on site i. Because we initially start with a sample centered only on the U.S., we use a measure of predicted forecast error variance fit as the criterion for selecting the function, g. Below we provide more details regarding the estimation procedure and motivation.

To motivate the interpretation of our approach as a GLS estimator, we must specify the variance-covariance matrix for the model's population error term, $u_i = y_i - x_i B$. A straightforward approach would be to assume a $(n \times n)$ diagonal error variance matrix,

$$\boldsymbol{\Omega} = diag[u_1^2, u_2^2, \dots, u_n^2]. \tag{8}$$

Where $E[(y_i - x_i B)^2] = u_i^2$ is assumed to be the known population variance for the error associated with observation i from the regression of Y on X and *diag[]* indicates elements of a diagonal matrix. Knowledge of this matrix allows us to calculate the efficient GLS estimator of B,

$$B_{gls} = (\boldsymbol{X}' \boldsymbol{\Omega}^{-1} \boldsymbol{X})^{-1} \boldsymbol{X}' \boldsymbol{\Omega}^{-1} Y. \tag{9}$$

Our approach diverges from the conventional GLS estimator because we assume that a potentially unique equation exists for each site i, according to equation (5). Thus we define for site i, the local variance for observation j, e_{ij}^2, such that,

$$E[(y_j - x_j B_j)^2] = e_{ij}^2. \tag{10}$$

Accordingly, for each site i, we can construct a local variance matrix, $\boldsymbol{\Omega}_i^{-1}$,

$$diag\left[u_{i1}^2, u_{i2}^2, \dots, u_{in}^2\right] = \boldsymbol{\Omega}_i^{-1} = \boldsymbol{\Omega}_i^{-1/2} \boldsymbol{\Omega}_i^{-1/2}, \tag{11}$$

which under the assumed variance structure allows for the consistent GLS estimate of B_i,

$$B_{gls_i} = (\boldsymbol{X}' \boldsymbol{\Omega}_i^{-1} \boldsymbol{X})^{-1} \boldsymbol{X}' \boldsymbol{\Omega}_i^{-1} Y. \tag{12}$$

The alternative interpretation of our estimator is based on the idea that an analyst can correct an observation that is overrepresented or underrepresented in the data with an inverse probability or frequency weight. Suppose that we know that an observation j under a random sampling mechanism will be drawn from the sub-population for site i with probability p_{ij}. Suppose we also know that drawing

observation j under a random sampling mechanism from the population of all observations is p_j. If we assume the sample of n observations is drawn from the general population of wetland valuation studies, then we can adjust the frequency of site j in the regression for site i by multiplying the row j of our data matrices Y and X by (p_{ij}/p_j) (Dumouchel and Duncan 1983). Accordingly, we treat the correction term the same as we would the variance, constructing the weight matrix, $\boldsymbol{\Omega}_i^{-1}$,

$$\boldsymbol{\Omega}_i^{-1} = diag\left[\left(\frac{p_{i1}}{p_1}\right)^2, \left(\frac{p_{i2}}{p_2}\right)^2, \dots, \left(\frac{p_{in}}{p_n}\right)^2\right]. \tag{13}$$

The fundamental problem with all WLS estimators is the unobservable nature of efficient weights. Below we detail an algorithmic approach to estimating weights, allowing for a potentially unique regression for each observation in the sample, designed for forecasting the dependent variable and providing an understanding of the validity of the forecast based on the correspondence between the forecast or policy site and each observation in the sample. The first step in understanding the algorithm behind our method is an explanation of how we formalize the idea of correspondence as a function of site attributes, discussed next.

One of the main advantages of estimating a regression centered on each site in the sample is that by doing so we can allow for variation in parameters as a site's correspondence attributes change relative to the sample. The typical regression models used in meta-analysis studies of ecosystem services do not estimate the wide variety of interaction effects that may exist among variables. The meta-analyses of wetland ecosystem services discussed above, with the exception of Ghermandi et al. (2010) do not discuss in much or any depth the possibility that these interaction effects exist. Because we have a complex sample, restricting the partial effects of regressors to be constant may lead to bias and inefficiency. The method we develop in this chapter is intended to improve on conventional approaches by allowing any observation to potentially have unique regression parameters, yet we are not required to estimate a potentially inefficient model filled with all possible interaction effects.

The process of locally calibrating weights involves the use of differences across cross-sectional observations. The econometric analysis of time series datasets frequently involves analysis of the difference in a variable over time; however, cross-sectional studies typically lack this feature because for cross-section data, no simple analog exists to the chronological ordering of time series variables. While we lack information indicating an empirical motivation for ordering observations, we can pay closer attention to the differences among observations in our dataset. The procedure we develop utilizes information about all n^2 differences among n observations. For each site, i, we can take the absolute difference between a correspondence attribute at site i (a_i) and site j (a_j) and arrange them in a column vector that will have n elements, the ith element will be zero. In order to allow for multiple correspondence attributes we also index attributes by $h = 1, \dots, H$. Thus for $h = 1$ we have a_{1i} and a_{1j}.

Next, we construct the *correspondence attribute difference* matrix $\boldsymbol{d}_i$. Equation (14) contains the matrix representation of $\boldsymbol{d}_i$. Each column represents a paraticular *correspondence attribute*, and each row represents the difference between an attribute at observation i and an attribute at another observation in the dataset.

$$\mathbf{d_i}=\begin{bmatrix} |a_{1i}-a_{11}| & |a_{2i}-a_{21}| & \dots & |a_{Hi}-a_{H1}| \\ |a_{1i}-a_{12}| & |a_{2i}-a_{22}| & \dots & |a_{Hi}-a_{H2}| \\ \vdots & \vdots & \ddots & \vdots \\ |a_{1i}-a_{1n}| & |a_{2i}-a_{2n}| & \dots & |a_{Hi}-a_{Hn}| \end{bmatrix} \tag{14}$$

A barrier arises when considering how H seemingly disparate attributes might be combined into a single measure of distance. The primary obstacle overcome by the algorithm below is the identification of correspondence coefficients that serve as normalizations on each correspondence attribute, which allows for a single measure of distance. Accordingly, we assume that there exists an $(H \times 1)$ correspondence coefficient vector, $\boldsymbol{\delta}$, composed of H scalar elements, $\delta_1, \dots, \delta_H$. This vector can be premultiplied by the $(n \times H)$ attribute difference matrix $\boldsymbol{d}_i$ to generate the argument for the function, $f(.)$ that returns a vector of weights used in the WLS regression for site i. Here we use equation $f(.)$ that takes the *correspondence attribute differences* as its argument rather than the similar function, $g(.)$ mentioned above. Equation (15) demonstrates this procedure for a single site, i. The next section details the procedure for identifying the correspondence coefficient vector, $\boldsymbol{\delta}$.

$$f(\boldsymbol{d}_i\boldsymbol{\delta}) =$$

$$f\left(\begin{bmatrix} |a_{1i}-a_{11}| & |a_{2i}-a_{21}| & \dots & |a_{Hi}-a_{H1}| \\ |a_{1i}-a_{12}| & |a_{2i}-a_{22}| & \dots & |a_{Hi}-a_{H2}| \\ \vdots & \vdots & \ddots & \vdots \\ |a_{1i}-a_{1n}| & |a_{2i}-a_{2n}| & \dots & |a_{Hi}-a_{Hn}| \end{bmatrix}\begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_H \end{bmatrix}\right) \tag{15}$$

$$= diag(\boldsymbol{\Omega}_i^{-1})$$

Here, diag(.) is an operator that returns a column vector of diagonal elements of a square matrix. When diag(.) is applied to a column vector, the result is a sparse matrix with the elements of the column vector on the diagonal and off diagonal elements are zero. The bottom line of equation (15) contains the WLS regression weights that are the fundamental source of potential divergence of parameter estimates across observations.

Detailed Exposition of the Calibration Procedure

The basic task of the calibration step requires estimation of the correspondence parameter vector, $\boldsymbol{\delta}$. In order to estimate empirical values for $\boldsymbol{\delta}$**,** we employ the Matlab constrained linear optimization algorithm, *fmincon*. While a variety of objective functions are potentially available for optimization, we pursue a GLS approach. While true GLS is not feasible for data with unknown variances, iterative strategies such as Feasible-GLS are available. The approach detailed below is an alternative to Feasible-GLS and requires no additional data. The variance of a random variable divided by its own standard deviation is equal to 1. Consequently, we choose as our objective function to minimize the sum of the squared distance between sample variances divided by their own estimated variance and 1. An analogous minimization procedure is to fit the sample variances to the parametric equation that predicts sample variances; this particular fit is what we detail below. The vector $\boldsymbol{WTP}_{(i)}$ containing $WTP_{(i)j}$ for $j = 1, \dots, n_i$ serves as the dependent variable in our main weighted regression equation, and we are interested in the case where $j = i$. Equation (16) contains the basic weighted regression model of interest.

$$\boldsymbol{\Omega}_i^{-½} WTP_{(i)i} = \boldsymbol{\Omega}_i^{-½} X_{(i)i} B_i + \boldsymbol{\Omega}_i^{-½} e_{(i)i} \tag{16}$$

The typical objective function is to choose the value for B_i that minimizes the sum of weighted sample residuals. In our model, we have an earlier step, which requires us to estimate the weights to be used in the regression for each observation. For each iteration of the first step optimization algorithm, correspondence parameters conjectures are used to develop the weights used in the regression. Specifically, we utilize the negative exponential function during calibration to specify the correspondence weight function, f, for the diagonal elements of the weight matrix, $\boldsymbol{\Omega}_i^{-1}$.

$$\widetilde{\boldsymbol{\Omega}}_{i\,jj}^{-1} = e^{-\sum_{h=1}^{H} |a_{hi} - a_{hj}| \widetilde{\delta}_h} = e^{-(|a_{1i} - a_{1j}| \widetilde{\delta}_1 + \cdots + |a_{Hi} - a_{Hj}| \widetilde{\delta}_H)} \tag{17}$$

In equation (17), which is equation $g(.)$ mentioned above, the jj subscript on $\widetilde{\boldsymbol{\Omega}}_i^{-1}$ indicates the jth row and jth column of the inverse of an estimate of the diagonal correspondence weight matrix $\boldsymbol{\Omega}$ for site i. For the final model we estimate, $|a_{Hi} - a_{Hj}|$ is actually estimated by using the Pythagorean Theorem with latitude and longitude to estimate geographic distance in 1000's of kilometers. The conjectured values for the correspondence parameters are used to estimate a weighted regression and residuals. If a valid model is chosen and the correspondence parameters are correctly chosen, the sample variance of weighted residuals can be expected to equal 1 on average, alternatively, the sample average of the residuals is expected to have the same variance as the inverse of the weight applied to that observation. Sample errors or residuals are found by first using a weighted regression to identify a parameter vector,

$$\tilde{B}_i = (\boldsymbol{X}_{(i)}{}'\widetilde{\boldsymbol{\Omega}}_i^{-1}\boldsymbol{X}_{(i)})^{-1}\boldsymbol{X}_{(i)}{}'\widetilde{\boldsymbol{\Omega}}_i^{-1}Y_{(i)} \tag{18}$$

And using this parameter to produce an $(n_i \times 1)$ unweighted vector of residuals, which when weighted will be close to 1 if the appropriate GLS-style weight has been applied in equation (4).

$$Y_{(i)} - \boldsymbol{X}_{(i)}\tilde{B}_i = \tilde{\boldsymbol{e}}_{(i)} \tag{19}$$

The objective function for the calibration step can then be written as it appears in equation (20). We further weight the residual from the variance calculation by the weight matrix, $\widetilde{\boldsymbol{\Omega}}_i^{-1}$, as there is less information in the sample error variance estimates for observations that are less precisely estimated by regression i.

$$\min_{\{\boldsymbol{\delta}\in\mathbb{R}^{\mathrm{H}}:\boldsymbol{\delta}\geq 0\}} \sum_{i=1}^{n} [(1_{n_i} - \widetilde{\boldsymbol{\Omega}}_i^{-1}\tilde{\boldsymbol{e}}_{(i)}^2)'\widetilde{\boldsymbol{\Omega}}_i^{-1}(1_{n_i} - \widetilde{\boldsymbol{\Omega}}_i^{-1}\tilde{\boldsymbol{e}}_{(i)}^2)] \tag{20}$$

Here 1_{n_i} indicates a column vector of 1's with n_i elements, and the squared term applies to each row of the vector of residuals.

In order to simplify estimation and to reduce the influence of ad-hoc constraints in our model, we require that for all values of $i = 1, \ldots,$ n, the data matrices $\boldsymbol{X}_{(i)}$ and $Y_{(i)}$ be identical in size, but with rows potentially weighted. Henceforth the (i) subscript denotes a data matrix that has row i removed, as we do not predict the centered observation's forecast error during calibration to avoid overfitting the model. The restriction that no observation can be fully dropped from a regression also entails that $n_i = n - 1$ for all i and that elements of $\tilde{B}_i$ are associated with the same correspondence attribute for all i. With the aid of substitution, equation (20) can be made more evident. Equation (21) contains an alternative version of the objective function to be minimized.

$$\sum_{i=1}^{n}[(diag(\widetilde{\boldsymbol{\Omega}}_i)-\tilde{\boldsymbol{e}}_{(i)}^2)'\widetilde{\boldsymbol{\Omega}}_i^{-1}(diag(\widetilde{\boldsymbol{\Omega}}_i)-\tilde{\boldsymbol{e}}_{(i)}^2)]$$

$$=\sum_{i=1}^{n}\left[\left(diag(\widetilde{\boldsymbol{\Omega}}_i)-\tilde{\boldsymbol{e}}_{(i)}^2\right)'\widetilde{\boldsymbol{\Omega}}_i^{-1}\left(diag(\widetilde{\boldsymbol{\Omega}}_i)-\tilde{\boldsymbol{e}}_{(i)}^2\right)\right] \tag{21}$$

$$=\sum_{i=1}^{n}\left[\left(\boldsymbol{diag}(\widetilde{\boldsymbol{\Omega}}_i)-(\boldsymbol{Y}_{(i)}-\boldsymbol{X}_{(i)}(\boldsymbol{X}_{(i)}'\widetilde{\boldsymbol{\Omega}}_i^{-1}\boldsymbol{X}_{(i)})^{-1}\boldsymbol{X}_{(i)}'\widetilde{\boldsymbol{\Omega}}_i^{-1}\boldsymbol{Y}_{(i)})^2\right)'\widetilde{\boldsymbol{\Omega}}_i^{-1}(\boldsymbol{diag}(\widetilde{\boldsymbol{\Omega}}_i)\right.$$
$$\left.-(\boldsymbol{Y}_{(i)}-\boldsymbol{X}_{(i)}(\boldsymbol{X}_{(i)}'\widetilde{\boldsymbol{\Omega}}_i^{-1}\boldsymbol{X}_{(i)})^{-1}\boldsymbol{X}_{(i)}'\widetilde{\boldsymbol{\Omega}}_i^{-1}\boldsymbol{Y}_{(i)})^2)\right]$$

Here $\widetilde{\boldsymbol{\Omega}}_i$ is a function of the correspondence parameter vector, $\boldsymbol{\delta}$. The highly non-linear nature in which the parameters enter the objective function requires numerical optimization. We employ a set of linear constraints through the *fmincon* Matlab routine for the correspondence parameters, as expressed in equation (22). In equation (22), $\boldsymbol{I}_H$ indicates an identity matrix with H diagonal elements, i.e., one for each correspondence parameter.

$$[\boldsymbol{A}_{min}][\delta]\leq[b_{min}]$$
$$[\boldsymbol{A}_{max}][\delta]\leq[b_{max}]$$
$$\boldsymbol{A}_{min}=-\boldsymbol{I}_H\ ,\boldsymbol{A}_{max}=\boldsymbol{I}_H$$
$$b_{min}=\begin{pmatrix}0\\0\\\vdots\\0\end{pmatrix},b_{max}=\begin{pmatrix}100\\100\\\vdots\\100\end{pmatrix} \tag{22}$$

Due to the linear restrictions defined in (22), parameter estimates will be neither non-negative nor large. The former restriction is implemented based on the theoretical notion that an increase in the distance between the correspondence attributes is expected to not provide additional information about the centered observation. The latter restriction was implemented to avoid searching for extremely large parameter values, which was useful for ensuring convergence. When we weight the data by multiplying correspondence parameters by correspondence attribute differences in the GLS equation, the maximum weight that can be obtained is 1, which for each regression is applied to the centered observation. We typically start the parameters in the optimization routine at zero, which results in all n models becoming conventional, evenly weighted OLS regressions. As a parameter value increases, the impact of an attribute distance on lowering an observation's weight also increases, as indicated in equation (23).

$$\frac{\partial\left(\mathbf{\Omega}_{\mathrm{ijj}}\right)}{\partial(\delta_h)} \leq 0$$
$$\frac{\partial\left(\mathbf{\Omega}_{\mathrm{ijj}}\right)}{\partial\left(\boldsymbol{d}_{i\,jh}\right)} \leq 0 \tag{23}$$

Where $\boldsymbol{d}_{i\,jh}$ denotes the jth row and h[th] column of the correspondence attribute distance matrix $\boldsymbol{d}_i$, found in equation (15). The equality in the first inequality of equation (23) holds when $i = j$ or when $a_{ih} = a_{jh}$; this partial derivative implies that as a correspondence parameter increases in magnitude for a given attribute distance between observations i and j, the membership of j in the population centered on i is reduced or that the variance of observation j in the neighborhood of observation i increases. Similarly, the second inequality in equation (23) is an equality when $\delta_h = 0$ or when $i = j$.

Post Calibration

The entire optimization procedure developed in the preceding section was used entirely for identifying the correspondence parameters, which apply to all n observations and all of their associated correspondence distances between the $n - 1$ remaining observations. From this point the next step is estimating regression parameters conditional on the correspondence parameters identified during the calibration step. While the centered regression parameters for all observations are implicitly estimated during the calibration step, a review of how to obtain these parameters for a given vector of correspondence attributes is useful for understanding how parameters are generated for out-of-sample forecasts.

For site i, the correspondence attribute distance matrix in equation (15) must be computed, next using the functional form specified in equation (17), where $f(.) = \mathrm{e}^{-(.)}$, correspondence attribute weights can be computed. Next the regression parameters for the centered site i can be computed by using OLS on the weighted data or equivalently by using WLS on the unweighted data but with the estimated diagonal correspondence weight matrix.

The process for generating a regression for an out-of-sample observation is precisely the same as above, with the exception that that correspondence attribute distance matrix, $\boldsymbol{d}_i$, (and its functional dependent, $\widetilde{\mathbf{\Omega}}_i$) is replaced by it's out-of-sample counterpart, $\boldsymbol{d}_{\sim i}$, where $\sim i$ indicates that the centered observation is not in the calibration dataset.

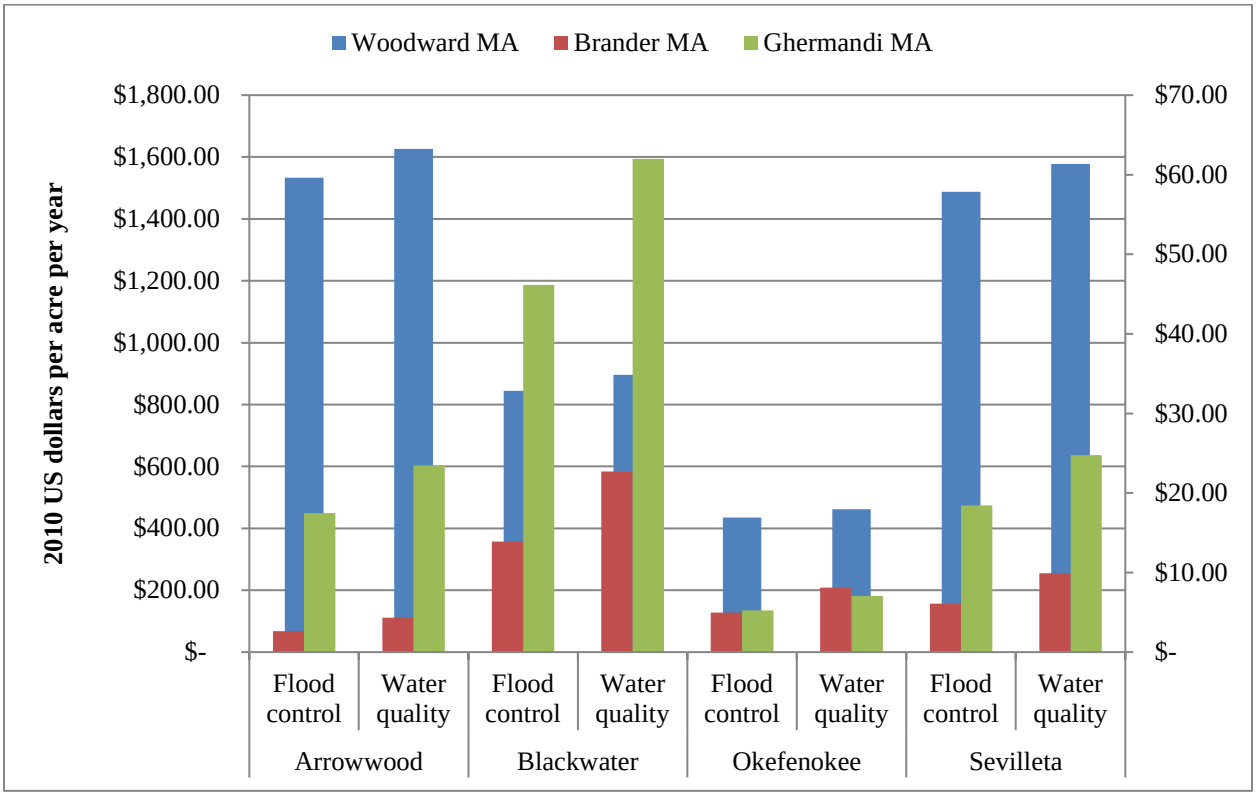
$$\boldsymbol{d}_{\sim i} = \begin{bmatrix} |\mathrm{a}_{1\sim i} - \mathrm{a}_{11}| & |\mathrm{a}_{2\sim i} - \mathrm{a}_{21}| & \dots & |\mathrm{a}_{H\sim i} - \mathrm{a}_{H1}| \\ |\mathrm{a}_{1\sim i} - \mathrm{a}_{12}| & |\mathrm{a}_{2\sim i} - \mathrm{a}_{22}| & \dots & |\mathrm{a}_{H\sim i} - \mathrm{a}_{H2}| \\ \vdots & \vdots & \ddots & \vdots \\ |\mathrm{a}_{1\sim i} - \mathrm{a}_{1n}| & |\mathrm{a}_{2\sim i} - \mathrm{a}_{2n}| & \dots & |\mathrm{a}_{H\sim i} - \mathrm{a}_{Hn}| \end{bmatrix} \tag{24}$$

The primary difference between $\boldsymbol{d}_i$ and $\boldsymbol{d}_{\sim i}$ is that the latter does not necessarily have zeros in all columns of the ith row. Analogously, $\boldsymbol{\Omega}_{\sim i}^{-1}$ differs from $\boldsymbol{\Omega}_i^{-1}$ in that the ith diagonal element is not necessarily equal to 1. The reason for this deviation is straightforward: during calibration the ith row of $\boldsymbol{d}_i$ is always the distance between observation i and itself, which is identically zero; post-calibration the centered observation is not included in the same manner. Because the attribute weight function is the negative exponential function, the ith diagonal element of $\widetilde{\boldsymbol{\Omega}}_i$ is $e^{-(0*\tilde{\delta}_1+0*\tilde{\delta}_2+\cdots+0*\tilde{\delta}_H)} = \mathrm{e}^{-0} = 1$. Once $\widetilde{\boldsymbol{\Omega}}_{\sim i}$ has been computed, the forecast for the out of sample observation is computed according to the expression in equation (25).

$$\begin{aligned} \tilde{Y}_i &= X_i \tilde{B}_i \\ \tilde{Y}_{\sim i} &= X_{\sim i}(\boldsymbol{X}'\widetilde{\boldsymbol{\Omega}}_{\sim i}^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'\widetilde{\boldsymbol{\Omega}}_{\sim i}^{-1}Y \end{aligned} \tag{25}$$

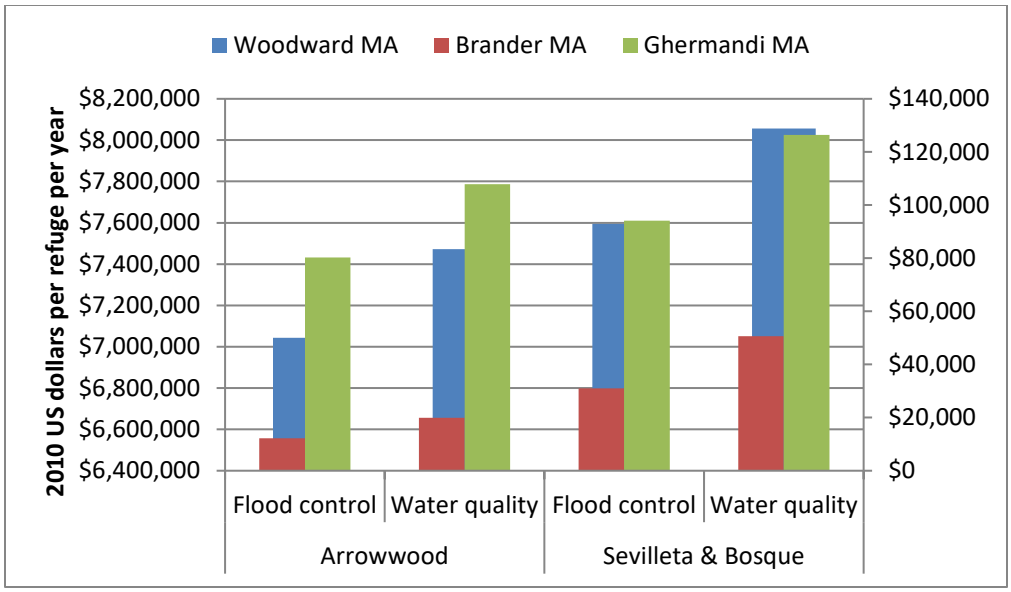
Notably, in equation (25) full data matrices are used to calculate the final regression parameter, $\tilde{B}_i$.

Figures and Tables



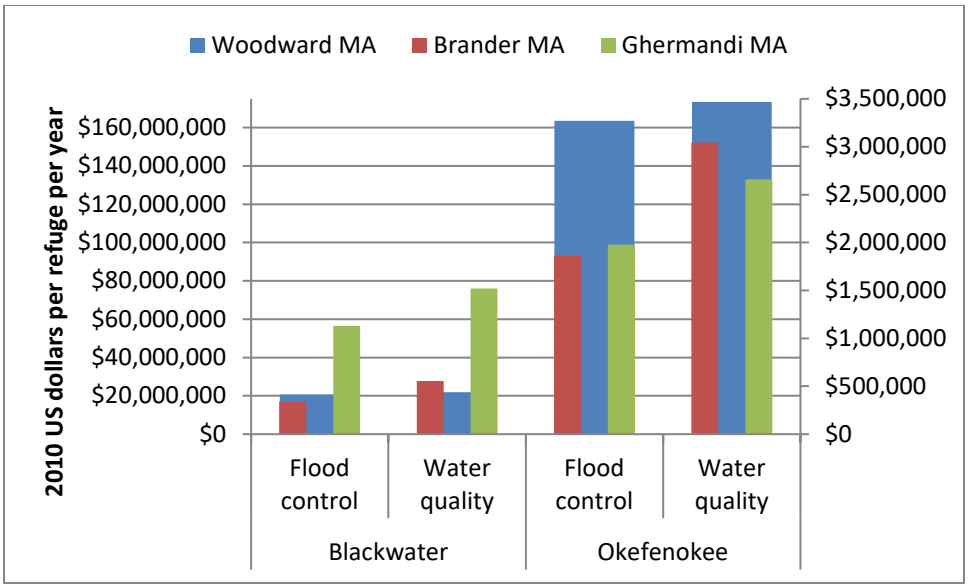
*Woodward and Wui 2001 values correspond to left side axis labels and Brander et al. (2006) and Ghermandi et al. (2010) values correspond to right side axis labels, all values 2010 US dollars per average acre per year

Figure 1: Point Estimates of Annual WTP per Average Acre by NWR Wetlands and Service



*Woodward and Wui 2001 values correspond to left side axis labels and Brander et al. (2006) and Ghermandi et al. (2010) values correspond to right side axis labels, all values 2010 US dollars for all refuge wetlands per year

Figure 2: Arrowwood and Sevilleta & Bosque NWR Point Estimates of WTP for Wetland Ecosystem Services, Aggregate Annual Values



*Woodward and Wui 2001 values correspond to left side axis labels and Brander et al. (2006) and Ghermandi et al. (2010) values correspond to right side axis labels, all values 2010 US dollars for all refuge wetlands per year

Figure 3: Blackwater and Okefenokee NWR Point Estimates of WTP for Wetland Ecosystem Services, Aggregate Annual Median Values

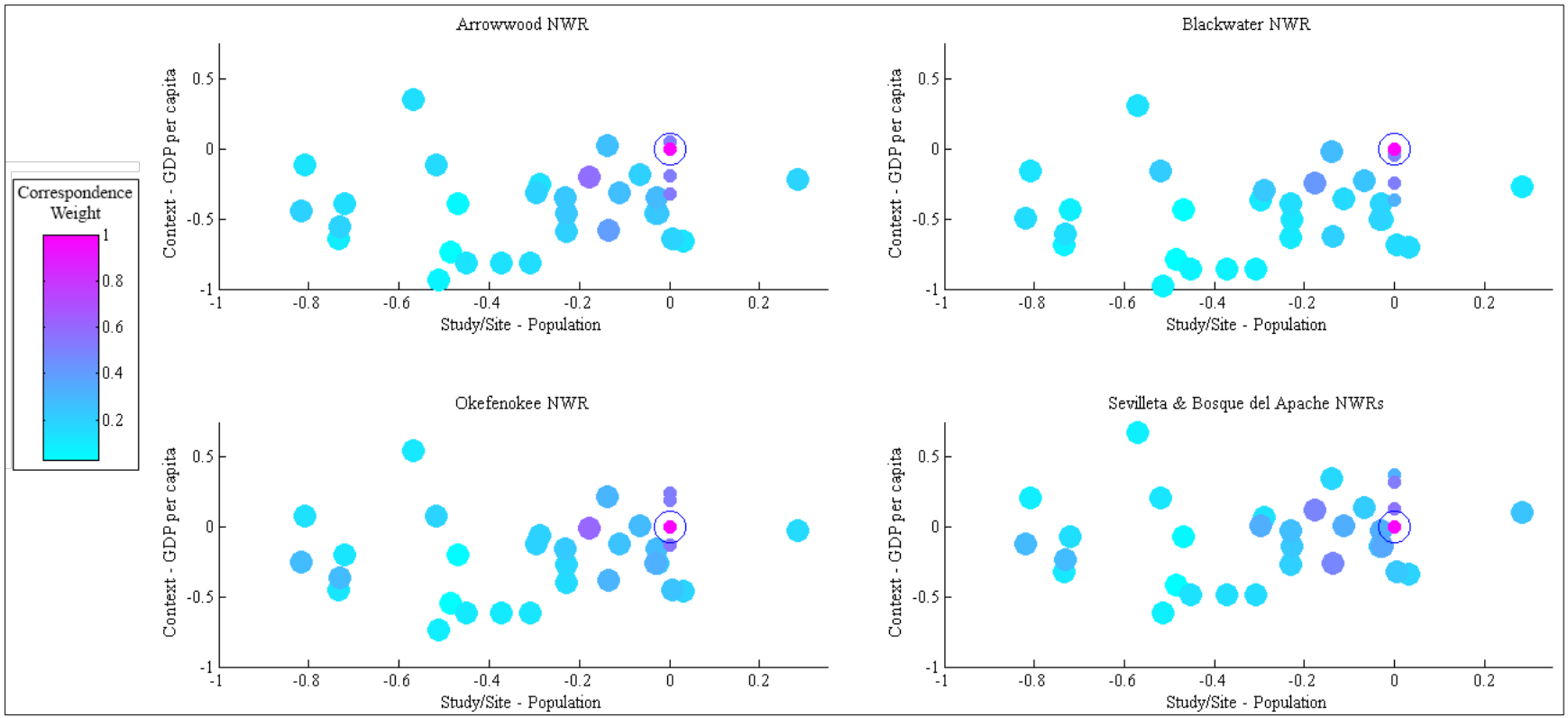


Figure 4: Plots of Correspondence Distance for 4 Case Study NWRs for stated preference water quality valuation.

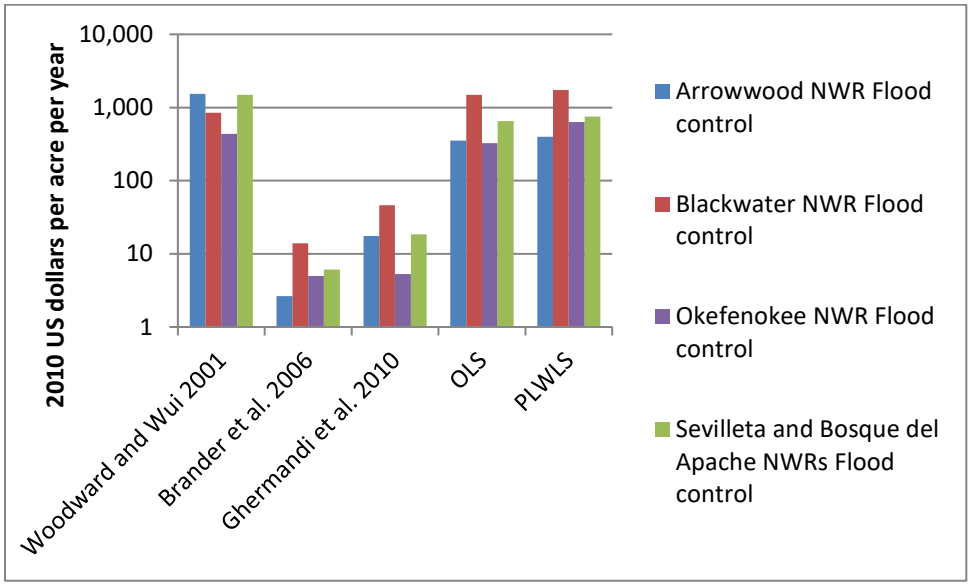


Figure 5: MA Forecast Comparison for Flood Control, Annual Median Value per Acre

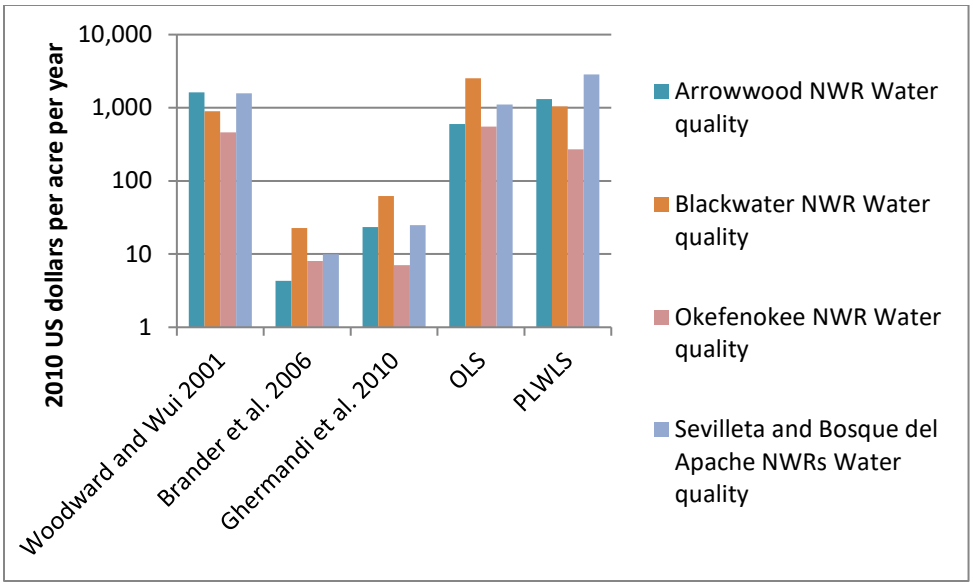


Figure 6: MA Forecast Comparison for Water Quality, Annual Value per Acre

Table 1: Variables Used in Three Published Wetland Ecosystem Services Meta-analyses.

	Woodward and Wui (2001) Model C	**Brander et al. (2006)**	**Ghermandi et al. (2010) Model B**
Landscape	Log (acres)	Log (hectares) Absolute value(latitude) Latitude^2 % of wetland identified as: Mangrove Unvegetated sediment Salt-brackish marsh Fresh marsh Woodland	Log (hectares) % of wetland identified as: Estuarine Marine Riverine Palustrine Lacustrine Human made dummy Wetland area in 50km radius
Geog. & socio-economic	Coastal indicator	Log (GDP per capita) Log (population density) Study location indicators: South America Europe Asia Africa Australasia Urban Ramsar proportion	Medium-low human pressure Medium-high human pressure High human pressure GDP per capita Population in 50km radius
Methodological	Year of publication Valuation method indicators: Hedonic Travel cost Replacement cost Net factor income Producer surplus	Marginal Valuation method indicators: Hedonic Travel cost Replacement cost Net factor income Contingent valuation Production function Market prices Opportunity cost	Marginal Year of publication
Service valued	Flood control Groundwater recharge Water quality Commercial fishing Recreational fishing Amenity Erosion reduction Bird watching Non-use appreciation of species	Flood control Water supply Water quality Commercial fishing and hunting Recreational fishing Recreational hunting Amenity Fuel wood Biodiversity Material	Flood control Surface/groundwater supply Water quality Comm. fishing and hunting Recreational fishing Recreational hunting Amenity and aesthetics Fuel wood Natural habitat, biodiversity Harvesting of natural materials Nonconsumptive recreation

Study quality	Published results Poor data quality Poor theory Poor econometrics		

Table 2: Variable Values for Arrowwood NWR Flood Control MABT with Each Published Meta-analysis.

Arrowwood NWR - Flood Control						
	Woodward and Wui (2001) Model C		**Brander et al. (2006)**		**Ghermandi et al. (2010) Model B**	
	Variable	*Value*	*Variable*	*Value*	*Variable*	*Value*
	Intercept	= 1	Intercept	= 1	Intercept	= 1
Landscape	Log acres	= 8.43	Log hectares	= 7.53	Log hectares	= 7.53
	-	-	Abs. val. Lat.	= 47.24	-	-
	-	-	Latitude^2	= 2231	-	-
Wetland type (ratios)	-	-	Fresh marsh Woodland All others	= 0.998 = 0.002 = 0	Palustrine Lacustrine Riverine All others	= 0.45 = 0.55 = 0.003 = 0
Socio-economic	-	-	Log (GDP per capita)	= 10.41	Log (GDP per capita)	= 10.59
	-	-	Log (Pop. Den.)	= -5.89	Log(Pop. in 50km)	= 9.99
	-	-	Ramsar Proportion	= 0	Human pressure indicators	= 0
Geog. indicators	Coastal	= 0	All	= 0	-	-
Method-ological	-	-	Marginal	= 0	Marginal	= 0
	Year of publication	= 52	-	-	Year of publication	= 36
Valuation method indicators	All	= 0	CV All others	= 1 =0	-	-
Services valued indicators	Flood control All others	= 1 = 0	Flood control All others	= 1 = 0	Flood control All others	= 1 = 0

Study quality indicators	All = 0	- -	- -

Table 3: Variable Values for Blackwater NWR Flood Control MABT with Each Published Meta-analysis.

Blackwater NWR - Flood Control						
	Woodward and Wui (2001) Model C		**Brander et al. (2006)**		**Ghermandi et al. (2010) Model B**	
	Variable	*Value*	*Variable*	*Value*	*Variable*	*Value*
	Intercept	= 1	Intercept	= 1	Intercept	= 1
Landscape	Log acres	= 10.11	Log hectares	= 9.20	Log hectares	= 9.20
	-	-	Abs. val. Lat.	= 38.4	-	-
	-	-	Latitude^2	= 1474.6	-	-
Wetland type (ratios)	-	-	Fresh marsh Woodland Salt-brackish marsh All others	= 0.01 = 0.40 = 0.59 = 0	Estuarine Palustrine Lacustrine Riverine	= 0.23 = 0.27 = 0.003 = .0006
Socio-economic	-	-	Log (GDP per capita)	= 10.55	Log (GDP per capita)	= 10.73
	-	-	Log (Pop. Den.)	= -3.47	Log(Pop. in 50km)	= 12.65
	-	-	Ramsar Proportion	= 1	Human pressure indicators	= 0
Geog. indicators	Coastal	= 0	All	= 0	-	-
Method-ological	-	-	Marginal	= 0	Marginal	= 0
	Year of publication	= 52	-	-	Year of publication	= 36
Valuation method indicators	All	= 0	CV All others	= 1 =0	-	-
Services valued indicators	Flood control All others	= 1 = 0	Flood control All others	= 1 = 0	Flood control All others	= 1 = 0
Study quality indicators	All	= 0	-	-	-	-

Table 4: Variable Values for Okefenokee NWR Flood Control MABT with Each Published Meta-analysis.

Okefenokee NWR - Flood Control						
	Woodward and Wui (2001) Model C		**Brander et al. (2006)**		**Ghermandi et al. (2010) Model B**	
	Variable	Value	Variable	Value	Variable	Value
	Intercept	= 1	Intercept	= 1	Intercept	= 1
Landscape	Log acres	= 12.84	Log hectares	= 11.9	Log hectares	= 11.9
	-	-	Abs. val. Lat.	= 30.84	-	-
	-	-	Latitude^2	= 950.92	-	-
Wetland type (ratios)	-	-	Fresh marsh Woodland All others	= 0.12 = 0.88 = 0	Palustrine Lacustrine Riverine All others	= 0.976 = 0.024 = .0004 = 0
Socio-economic	-	-	Log (GDP per capita)	= 10.27	Log (GDP per capita)	= 10.45
	-	-	Log (Pop. Den.)	= -5.60	Log(Pop. in 50km)	= 10.95
	-	-	Ramsar Proportion	= 1	Human pressure indicators	= 0
Geog. indicators	Coastal	= 0	All	= 0	-	-
Method-ological	-	-	Marginal	= 0	Marginal	= 0
	Year of publication	= 52	-	-	Year of publication	= 36
Valuation method indicators	All	= 0	CV All others	= 1 =0	-	-
Services valued indicators	Flood control All others	= 1 = 0	Flood control All others	= 1 = 0	Flood control All others	= 1 = 0
Study quality indicators	All	= 0	-	-	-	-

Table 5: Variable Values for Sevilleta and Bosque del Apache NWRs Flood Control MABT with Each Published Meta-analysis.

Sevilleta & Bosque del Apache NWRs - Flood Control						
	Woodward and Wui (2001) Model C		**Brander et al. (2006)**		**Ghermandi et al. (2010) Model B**	
	Variable	Value	Variable	Value	Variable	Value
	Intercept	= 1	Intercept	= 1	Intercept	= 1
Landscape	Log acres	= 8.54	Log hectares	= 7.63	Log hectares	= 7.63
	-	-	Abs. val. Lat.	= 34.05	-	-
	-	-	Latitude^2	= 1159.6	-	-
Wetland type (ratios)	-	-	Fresh marsh Woodland All others	= 0.79 = 0.21 = 0	Palustrine Lacustrine Riverine All others	= 0.575 = 0.062 = 0.363 = 0
Socio-economic	-	-	Log (GDP per capita)	= 10.24	Log (GDP per capita)	= 10.42
	-	-	Log (Pop. Den.)	= -5.45	Log(Pop. in 50km)	= 10.24
	-	-	Ramsar Proportion	= 0	Human pressure indicators	= 0
Geog. indicators	Coastal	= 0	All	= 0	-	-
Method-ological	-	-	Marginal	= 0	Marginal	= 0
	Year of publication	= 52	-	-	Year of publication	= 36
Valuation method indicators	All	= 0	CV All others	= 1 =0	-	-
Services valued indicators	Flood control All others	= 1 = 0	Flood control All others	= 1 = 0	Flood control All others	= 1 = 0
Study quality indicators	All	= 0	-	-	-	-

Table 6 MA Data Summary

Variable	Mean	Variance
n=82		
Dependent		
Value/1000ac/pop†	24.29416996	13584.72966
Study/Site		
Acres valued†	154934.3668	2.29501E+11
Population†	3531250.744	5.66455E+13
Methodological (1/0)		
Valuation Approach		
Revealed preference	0.18293	0.15131
Stated preference	0.73171	0.19874
Joint valuation (1,2,3)	1.1098	0.17299
Service Valued		
Water quality	0.12195	0.1084
Flood protection	0.060976	0.057964
Total value	0.5	0.25309
Recreation, general	0.12195	0.1084
Habitat	0.085366	0.079042
Recreation, fishing	0.02439	0.024089
Recreation, hunting	0.15854	0.13505
Interaction_use	0.073171	0.068654
Interaction_passive	0.20732	0.16637
Context		
GDP(state)†	31205.5105	37717998.95
Coastal (1/0)	0.12195	0.1084
GDP*local_pop†	25825016098	2.01947E+21
Local_pop:local_wet†	47.06399473	0.057448
† mean and variance in levels, but variable used in log form		

Table 7: Arrowwood NWR MABT Monte Carlo Quantiles

	Arrowwood NWR	Predicted per-acre value, $e^{E[X\beta]}$	Simulated distribution of expected per-acre value		
			5th percentile	50th percentile	95th percentile
Flood Control	Woodward and Wui	1532.83	4.56	1528.94	513829.36
	Brander et al.	2.65	0.0000005	2.61	14011026.33
	Ghermandi et al.	17.48	0.19	17.56	1634.44
	Precision weighted average	17.49			
	Unweighted average	517.66			
Water Quality	Woodward and Wui	1625.99	4.89	1621.53	544059.38
	Brander et al.	4.33	0.0000008	4.28	23459222.04
	Ghermandi et al.	23.48	0.25	23.58	2176.20
	Precision weighted average	23.49			
	Unweighted average	551.27			

Table 8: Blackwater NWR MABT Monte Carlo Quantiles

	Blackwater NWR	Predicted per-acre value, $e^{E[X\beta]}$	Simulated distribution of expected per-acre value		
			5th percentile	50th percentile	95th percentile
Flood Control	Woodward and Wui	844.86	1.90	843.77	370704.19
	Brander et al.	13.91	0.0000057	13.75	34432273.25
	Ghermandi et al.	46.16	0.42	46.43	5155.70
	Precision weighted average	46.17			
	Unweighted average	301.64			
Water Quality	Woodward and Wui	896.22	2.05	893.67	392006.84
	Brander et al.	22.70	0.0000090	22.38	58489215.98
	Ghermandi et al.	62.00	0.56	62.36	6918.91
	Precision weighted average	62.03			
	Unweighted average	326.97			

Table 9: Okefenokee NWR MABT Monte Carlo Quantiles

	Okefenokee NWR	Predicted per-acre value, $e^{E[X\beta]}$	Simulated distribution of expected per-acre value		
			5th percentile	50th percentile	95th percentile
Flood Control	Woodward and Wui	435.00	0.89	433.94	209566.46
	Brander et al.	4.96	0.0000037	4.91	6702403.62
	Ghermandi et al.	5.27	0.05	5.29	550.86
	Precision weighted average	5.27			
	Unweighted average	148.41			
Water Quality	Woodward and Wui	461.42	0.97	460.82	221840.58
	Brander et al.	8.09	0.0000058	8.01	11151922.26
	Ghermandi et al.	7.07	0.07	7.11	741.71
	Precision weighted average	7.07			
	Unweighted average	158.86			

Table 10: Sevilleta & Bosque del Apache NWRs MABT Monte Carlo Quantiles

	Sevilleta & Bosque del Apache NWRs	Predicted per-acre value, $e^{E[X\beta]}$	Simulated distribution of expected per-acre value		
			5th percentile	50th percentile	95th percentile
Flood Control	Woodward and Wui	1487.34	4.39	1483.62	501931.60
	Brander et al.	6.07	0.0000041	6.00	8991305.62
	Ghermandi et al.	18.44	0.20	18.51	1666.25
	Precision weighted average	18.44			
	Unweighted average	503.95			
Water Quality	Woodward and Wui	1577.75	4.71	1572.97	531797.40
	Brander et al.	9.91	0.0000065	9.77	15247340.97
	Ghermandi et al.	24.76	0.28	24.89	2227.39
	Precision weighted average	24.76			
	Unweighted average	537.47			

Table 11: Flood Control Monte Carlo Mean and Variance

Flood control	**dollars per acre per year**			
Refuge	**Mean, E[exp(Xβ)]**		**Var(exp(Xβ))**	
Arrowwood NWR	Woodward	1.20E+05	Woodward	1.67E+07
	Brander	1.04E+11	Brander	3.15E+21
	Ghermandi	258.391783	Ghermandi	21.91413
Blackwater NWR	Woodward	1.00E+05	Woodward	2.15E+07
	Brander	1.32E+11	Brander	8.83E+21
	Ghermandi	848.180639	Ghermandi	290.9219
Okefenokee NWR	Woodward	6.16E+04	Woodward	1.17E+07
	Brander	4.73E+09	Brander	1.93E+18
	Ghermandi	89.7147602	Ghermandi	3.29932
Sevilleta & Bosque del Apache NWRs	Woodward	1.18E+05	Woodward	1.65E+07
	Brander	7.30E+09	Brander	3.58E+18
	Ghermandi	261.248864	Ghermandi	18.64035

Table 12: Water Quality Monte Carlo Mean and Variance

Water quality	**dollars per acre per year**			
Refuge	**Mean, E[exp(Xβ)]**		**Var(exp(Xβ))**	
Arrowwood NWR	Woodward	1.31E+05	Woodward	2.65E+07
	Brander	2.40E+11	Brander	1.59E+22
	Ghermandi	343.298878	Ghermandi	34.22148
Blackwater NWR	Woodward	1.05E+05	Woodward	1.81E+07
	Brander	2.91E+11	Brander	4.25E+22
	Ghermandi	1127.29233	Ghermandi	513.977242
Okefenokee NWR	Woodward	6.64E+04	Woodward	1.54E+07
	Brander	9.37E+09	Brander	8.79E+18
	Ghermandi	119.018048	Ghermandi	4.797655909
Sevilleta & Bosque del Apache NWRs	Woodward	1.28E+05	Woodward	2.61E+07
	Brander	1.54E+10	Brander	2.72E+19
	Ghermandi	348.017512	Ghermandi	31.16060726

Table 13: Estimated WTP per Average Acre per Year and for Refuge Wetlands per Year

`			median value per average acre	NWI wetland acres	median value per refuge
Woodward and Wui 2001	Arrowwood NWR	Flood control	$1,533	*4,595*	$7,044,000
		Water quality	$1,626	4,595	$7,472,000
	Blackwater NWR	Flood control	$845	24,502	$20,700,000
		Water quality	$896	24,502	$21,959,000
	Okefenokee NWR	Flood control	$435	375,778	$163,462,000
		Water quality	$461	375,778	$173,393,000
	Sevilleta & Bosque NWRs	Flood control	$1,487	5,106	$7,594,000
		Water quality	$1,578	5,106	$8,056,000
Brander et al. 2006	Arrowwood NWR	Flood control	$2.65	*4,595*	$12,200
		Water quality	$4.33	4,595	$19,900
	Blackwater NWR	Flood control	$13.91	24,502	$341,000
		Water quality	$22.70	24,502	$556,000
	Okefenokee NWR	Flood control	$4.96	375,778	$1,863,000
		Water quality	$8.09	375,778	$3,042,000
	Sevilleta & Bosque NWRs	Flood control	$6.07	5,106	$31,000
		Water quality	$9.91	5,106	$50,600
Ghermandi et al. 2010	Arrowwood NWR	Flood control	$17.48	*4,595*	$80,300
		Water quality	$23.48	4,595	$107,900
	Blackwater NWR	Flood control	$46.16	24,502	$1,131,000
		Water quality	$62.00	24,502	$1,519,000
	Okefenokee NWR	Flood control	$5.27	375,778	$1,979,000
		Water quality	$7.07	375,778	$2,659,000
	Sevilleta & Bosque NWRs	Flood control	$18.44	5,106	$94,100
		Water quality	$24.76	5,106	$126,400

Table 14: OLS MA Regression Model Results

Variable	OLS Coefficient	standard error	T-statistic	P-value
Intercept	24.147	19.863	1.216	0.23
Study/Site				
Acres valued†	-0.583*	0.306*	-1.904	0.06
Population†	-0.41***	0.148***	-2.761	0.01
Methodological (1/0)				
Valuation Approach				
Revealed preference	-4.401*	2.319*	-1.898	0.06
Stated preference	0.864	1.305	0.662	0.51
Joint valuation (1,2,3)	-5.977***	1.435***	-4.164	0
Service Valued				
Water quality	5.969**	2.864**	2.084	0.04
Flood protection	5.438*	2.861*	1.9	0.06
Total value	6.534**	2.836**	2.304	0.02
Recreation, general	10.667***	2.627***	4.061	0
Habitat	6.564**	3.093**	2.122	0.04
Recreation, fishing	5.287**	2.178**	2.428	0.02
Recreation, hunting	5.011*	2.628*	1.907	0.06
Interaction_use	-1.211**	0.562**	-2.153	0.04
Interaction_passive	-0.705	0.56	-1.258	0.21
Context				
GDP(state)†	-2.681	2.076	-1.291	0.2
Coastal (1/0)	1.214**	0.566**	2.144	0.04
GDP*local_pop†	0.038	0.029	1.309	0.2
Local_pop:local_wet†	2.394**	1.124**	2.13	0.04
$R^2 = 0.81$				
Significance levels: ***<0.01, **<0.05, *<0.1				

Table 15: PLWLS Estimated Correspondence Parameters

Correspondence Attribute	**Estimated Correspondence Parameter**
Flood control	1.365992
GDP	1.276706
Water quality	0.760224
Coastal	0.218638
Distance 10^3km	0.194442
Population	0.133756
Acres	0

Table 16: Arrowwood NWR Stated Preference Water Quality, Ten Highest Correspondence Observations

Arrowwood NWR	Stated Pref.	Water quality	$42,500	0 km	3,531,251	N/A
Author-date	**Method**	**Service valued**	**GDP per capita**	**Euclidean distance**	**Study pop.**	**Regression Weight**
Bishop et al. 2000	Stated pref.	Water quality	$36,200	917	936,090	2.7697
Bishop et al. 2000	Stated pref.	Water quality	$36,200	917	936,090	2.7697
Bishop et al. 2000	Stated pref.	Water quality	$36,200	917	936,090	2.7697
Sutherland & Walsh 1985	Stated pref.	Water quality, use value	$27,000	1162	1,275,514	1.8876
Sutherland & Walsh 1985	Stated pref.	Water quality bequest value	$27,000	1162	1,275,514	1.8876
Sutherland & Walsh 1985	Stated pref.	Water quality exist. value	$27,000	1162	1,275,514	1.8876
Sutherland & Walsh 1985	Stated pref.	Water quality option value	$27,000	1162	1,275,514	1.8876
Sutherland & Walsh 1985	Stated pref.	Water quality total value	$27,000	1162	1,275,514	1.8876
Phaneuf & Herriges 1999	Revealed pref.	Recreation	$32,300	645	630,561	1.3689
Phaneuf & Herriges 1999	Revealed pref.	Recreation	$32,300	721	630,561	1.3488

Table 17: Blackwater NWR Stated Preference Water Quality, Ten Highest Correspondence Observations

Blackwater NWR	Stated Pref.	Water quality	$44,000	0 km	3,531,251	N/A
Author-date	**Method**	**Service valued**	**GDP per capita**	**Euclidean distance**	**Study pop.**	**Regression Weight**
Bishop et al. 2000	Stated pref.	Water quality	$36,200	1180	936,090	2.8578
Bishop et al. 2000	Stated pref.	Water quality	$36,200	1180	936,090	2.8578
Bishop et al. 2000	Stated pref.	Water quality	$36,200	1180	936,090	2.8578
Beran 1995	Stated pref.	Total value	$43,300	695	1,258,753	1.9196
Petrolia & Kim 2011	Stated pref.	Total value	$36,800	1702	2,146,273	1.7119
Bauer, Cyr, & Swallow 2004	Stated pref.	Total value	$34,800	512	408,000	1.6123
Bauer, Cyr, & Swallow 2004	Stated pref.	Total value	$34,800	512	408,000	1.6123
Bauer, Cyr, & Swallow 2004	Stated pref.	Total value	$34,800	512	408,000	1.6123
Bauer, Cyr, & Swallow 2004	Stated pref.	Total value	$34,800	512	408,000	1.6123
Johnston et al. 2002	Stated pref.	Total value	$38,800	433	73,423	1.4913

Table 18: Okefenokee NWR Stated Preference Water Quality, Ten Highest Correspondence Observations

Okefenokee NWR	Stated Pref.	Water quality	$36,400	0 km	3,531,251	N/A
Author-date	**Method**	**Service valued**	**GDP per capita**	**Euclidean distance**	**Study pop.**	**Regression Weight**
Bishop et al. 2000	Stated pref.	Water quality	$36,200	1632	936,090	2.8787
Bishop et al. 2000	Stated pref.	Water quality	$36,200	1632	936,090	2.8787
Bishop et al. 2000	Stated pref.	Water quality	$36,200	1632	936,090	2.8787
MacDonald, Bergstrom, & Houston 1998	Stated pref.	Habitat	$29,700	319	2,793,672	1.5584
Sutherland & Walsh 1985	Stated pref.	Water quality, use value	$27,000	3298	1,275,514	1.4882
Sutherland & Walsh 1985	Stated pref.	Water quality bequest value	$27,000	3298	1,275,514	1.4882
Sutherland & Walsh 1985	Stated pref.	Water quality exist. value	$27,000	3298	1,275,514	1.4882
Sutherland & Walsh 1985	Stated pref.	Water quality option value	$27,000	3298	1,275,514	1.4882
Sutherland & Walsh 1985	Stated pref.	Water quality total value	$27,000	3298	1,275,514	1.4882
Beran 1995	Stated pref.	Total value	$43,300	326	1,258,753	1.4581

Table 19: Sevilleta & Bosque del Apache NWRs Stated Preference Water Quality, Ten Highest Correspondence Observations

Sevilleta & Bosque del Apache NWRs	Stated Pref.	Water quality	$32,900	0 km	3,531,251	N/A
Author-date	**Method**	**Service valued**	**GDP per capita**	**Euclidean distance**	**Study pop.**	**Regression Weight**
Bishop et al. 2000	Stated pref.	Water quality	$36,200	2040	936,090	1.936
Bishop et al. 2000	Stated pref.	Water quality	$36,200	2040	936,090	1.936
Bishop et al. 2000	Stated pref.	Water quality	$36,200	2040	936,090	1.936
Sutherland & Walsh 1985	Stated pref.	Water quality, use value	$27,000	1662	1,275,514	1.8982
Sutherland & Walsh 1985	Stated pref.	Water quality bequest value	$27,000	1662	1,275,514	1.8982
Sutherland & Walsh 1985	Stated pref.	Water quality exist. value	$27,000	1662	1,275,514	1.8982
Sutherland & Walsh 1985	Stated pref.	Water quality option value	$27,000	1662	1,275,514	1.8982
Sutherland & Walsh 1985	Stated pref.	Water quality total value	$27,000	1662	1,275,514	1.8982
Sanders, Walsh, & McKean 1991	Revealed pref.	Recreation	$29,600	566	2,889,964	1.3836
Sanders, Walsh, & Loomis 1990	Stated pref.	Total use value	$29,600	566	2,889,964	1.3836

Table 20: Arrowwood NWR Stated Preference Flood control, Ten Highest Correspondence Observations

Arrowwood NWR	Stated Pref.	Flood control	$42,500	0 km	3,531,251	N/A
Author-date	**Method**	**Service valued**	**GDP per capita**	**Euclidean distance**	**Study pop.**	**Regression Weight**
Leitch and Hoyde 1996	Damage avoidance	Flood control	$26,700	98	638,800	3.8413
Leitch and Hoyde 1996	Damage avoidance	Flood control & habitat	$26,700	145	638,800	3.8062
Roberts and Leitch 1997	Damage avoidance	Flood control & habitat	$31,300	233	106,406	3.6005
Roberts and Leitch 1997	Damage avoidance	Flood control	$31,300	235	106,406	3.5993
Costanza, Farber, & Maxwell 1989	Damage avoidance	Flood control	$23,800	2116	94,393	1.3931
Phaneuf & Herriges 1999	Revealed pref.	Recreation	$32,300	645	630,561	1.371
Phaneuf & Herriges 1999	Revealed pref.	Recreation	$32,300	721	630,561	1.3509
Poor 1999	Stated pref.	Total value	$33,200	739	1,541,253	1.2821
Beran 1995	Stated pref.	Total value	$43,300	2205	1,258,753	1.2542
Sanders, Walsh, & Loomis 1990	Stated pref.	Total use value	$29,600	1034	2,889,964	1.1417

Table 21: Blackwater NWR Stated Preference Flood control, Ten Highest Correspondence Observations

Blackwater NWR	Stated Pref.	Flood control	$44,000	0 km	3,531,251	N/A
Author-date	**Method**	**Service valued**	**GDP per capita**	**Euclidean distance**	**Study pop.**	**Regression Weight**
Leitch and Hoyde 1996	Damage avoidance	Flood control	$26,700	1991	638,800	2.9085
Roberts and Leitch 1997	Damage avoidance	Flood control & habitat	$31,300	1867	106,406	2.8671
Roberts and Leitch 1997	Damage avoidance	Flood control	$31,300	1872	106,406	2.864
Leitch and Hoyde 1996	Damage avoidance	Flood control & habitat	$26,700	2191	638,800	2.7972
Costanza, Farber, & Maxwell 1989	Damage avoidance	Flood control	$23,800	1689	94,393	2.5647
Beran 1995	Stated pref.	Total value	$43,300	695	1,258,753	1.937
Petrolia & Kim 2011	Stated pref.	Total value	$36,800	1702	2,146,273	1.7274
Bauer, Cyr, & Swallow 2004	Stated pref.	Total value	$34,800	512	408,000	1.627
Bauer, Cyr, & Swallow 2004	Stated pref.	Total value	$34,800	512	408,000	1.627
Bauer, Cyr, & Swallow 2004	Stated pref.	Total value	$34,800	512	408,000	1.627

Table 22: Okefenokee NWR Stated Preference Flood control, Ten Highest Correspondence Observations

Okefenokee NWR	Stated Pref.	Flood control	$36,400	0 km	3,531,251	N/A
Author-date	**Method**	**Service valued**	**GDP per capita**	**Euclidean distance**	**Study pop.**	**Regression Weight**
Leitch and Hoyde 1996	Damage avoidance	Flood control	$26,700	2217	638,800	3.0917
Roberts and Leitch 1997	Damage avoidance	Flood control	$31,300	2079	106,406	3.0558
Roberts and Leitch 1997	Damage avoidance	Flood control & habitat	$31,300	2082	106,406	3.0541
Leitch and Hoyde 1996	Damage avoidance	Flood control & habitat	$26,700	2453	638,800	2.953
Costanza, Farber, & Maxwell 1989	Damage avoidance	Flood control	$23,800	839	94,393	2.1704
MacDonald, Bergstrom, & Houston 1998	Stated pref.	Habitat	$29,700	319	2,793,672	1.5883
Beran 1995	Stated pref.	Total value	$43,300	326	1,258,753	1.4861
Petrolia & Kim 2011	Stated pref.	Total value	$36,800	870	2,146,273	1.422
Phaneuf & Herriges 1999	Revealed pref.	Recreation	$32,300	1596	630,561	1.3848
Phaneuf & Herriges 1999	Revealed pref.	Recreation	$32,300	1674	630,561	1.3639

Table 23: Sevilleta & Bosque del Apache NWRs Stated Preference Flood control, Ten Highest Correspondence Observations

Sevilleta & Bosque del Apache NWRs	Stated Pref.	Flood control	$32,900	0 km	3,531,251	N/A
Author-date	**Method**	**Service valued**	**GDP per capita**	**Euclidean distance**	**Study pop.**	**Regression Weight**
Leitch and Hoyde 1996	Damage avoidance	Flood control	$26,700	1604	638,800	3.1907
Leitch and Hoyde 1996	Damage avoidance	Flood control & habitat	$26,700	1714	638,800	3.123
Roberts and Leitch 1997	Damage avoidance	Flood control	$31,300	1563	106,406	3.0947
Roberts and Leitch 1997	Damage avoidance	Flood control & habitat	$31,300	1580	106,406	3.0848
Costanza, Farber, & Maxwell 1989	Damage avoidance	Flood control	$23,800	1600	94,393	1.7147
Sanders, Walsh, & McKean 1991	Revealed pref.	Recreation	$29,600	566	2,889,964	1.3919
Sanders, Walsh, & Loomis 1990	Stated pref.	Total use value	$29,600	566	2,889,964	1.3919
Sanders, Walsh, & Loomis 1990	Stated pref.	Total exist. value	$29,600	566	2,889,964	1.3919
Sanders, Walsh, & Loomis 1990	Stated pref.	Total option value	$29,600	566	2,889,964	1.3919
Sanders, Walsh, & Loomis 1990	Stated pref.	Total bequest value	$29,600	566	2,889,964	1.3919

Table 24: OLS and PLWLS Forecasts for 4 NWRs, Annual dollars per 1000 Acres per 1000 People per Year

2010 US dollars per 1000 acres per 1000 people per year		OLS		PLWLS	
Site	Service Valued	Median $\exp(XB_i)$	Mean $\exp(XB_i)$	Median $\exp(XB_i)$	Mean $\exp(XB_i)$
Arrowwood NWR	WQ	$170	$520	$370	$450
	FC	$100	$310	$110	$130
Blackwater NWR	WQ	$720	$2,210	$290	$330
	FC	$420	$1,300	$490	$550
Okefenokee NWR	WQ	$160	$480	$80	$90
	FC	$90	$280	$180	$210
Sevilleta & Bosque del Apache NWRs	WQ	$320	$970	$810	$980
	FC	$190	$570	$210	$260

Table 25: OLS and PLWLS Aggregate Values for 4 NWRs

Aggregate Annual Value 2010 US Dollars per Refuge per Year						
Site	Service Valued	acres	OLS median	OLS mean	PLWLS median	PLWLS mean
Arrowwood NWR	WQ	4,595	2,767,000	8,508,000	6,043,000	7,229,000
	FC		1,626,000	5,000,000	1,830,000	2,165,000
Blackwater NWR	WQ	24,502	62,294,000	191,523,000	25,479,000	28,748,000
	FC		36,606,000	112,547,000	42,653,000	47,530,000
Okefenokee NWR	WQ	375,778	208,374,000	640,647,000	101,817,000	120,588,000
	FC		122,450,000	376,474,000	238,576,000	279,353,000
Sevilleta & Bosque del Apache NWRs	WQ	5,106	5,682,000	17,468,000	14,551,000	17,661,000
	FC		3,339,000	10,265,000	3,838,000	4,625,000

Table 26: Comparison of 5 MA Models for 4 NWRs, Flood Control

2010 US Dollars per Year for NWR Wetlands					
Arrowwood NWR					
Flood control					
	Woodward	Brander	Ghermandi	OLS	PLWLS
Median	7,043,776	12,177	80,325	1,626,115	1,830,089
Mean	553,429,493	4.780E+14	1,187,381	4,999,561	**2,165,016**
Blackwater NWR					
Flood control					
	Woodward	Brander	Ghermandi	OLS	PLWLS
Median	20,700,411	340,817	1,130,993	36,606,278	42,653,249
Mean	2,450,105,399	3.228E+15	20,781,772	112,546,849	**47,529,586**
Okefenokee NWR					
Flood control					
	Woodward	Brander	Ghermandi	OLS	PLWLS
Median	163,463,577	1,863,861	1,980,352	122,449,919	238,575,511
Mean	2.32E+10	1.78E+15	33,712,864	376,473,987	**279,353,226**
Sevilleta & Bosque del Apache NWRs					
Flood control					
	Woodward	Brander	Ghermandi	OLS	PLWLS
Median	7,594,007	30,992	94,150	3,338,566	3,837,809
Mean	603,359,646	3.73E+13	1,333,875	10,264,508	**4,624,627**

Table 27 Comparison of 5 MA Models for 4 NWRs, Water Quality

2010 US Dollars per Year for NWR Wetlands					
Arrowwood NWR					
Water quality					
	Woodward	Brander	Ghermandi	OLS	PLWLS
Median	7,471,872	19,898	107,897	2,767,365	6,043,124
Mean	600,924,752	1.102E+15	1,577,553	8,508,016	**7,229,323**
Blackwater NWR					
Water quality					
	Woodward	Brander	Ghermandi	OLS	PLWLS
Median	21,958,813	556,186	1,519,098	62,294,439	25,478,779
Mean	2,581,881,606	7.131E+15	27,620,452	191,523,451	**28,747,552**
Okefenokee NWR					
Water quality					
	Woodward	Brander	Ghermandi	OLS	PLWLS
Median	173,391,641	3,040,047	2,656,753	208,373,728	101,816,900
Mean	2.50E+10	3.52E+15	44,724,404	640,646,704	**120,588,184**
Sevilleta & Bosque del Apache NWRs					
Water quality					
	Woodward	Brander	Ghermandi	OLS	PLWLS
Median	8,055,619	50,598	126,419	5,681,530	14,550,536
Mean	655,118,693	7.85E+13	1,776,895	17,467,567	**17,661,387**