Land Value Impacts of Wetland Restoration

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Abstract

U.S. regulations require offsets for aquatic ecosystems damaged during land development, often through restoration of alternative resources. What effect does large scale wetland and stream restoration have on surrounding land values? Restoration effects on real estate values have substantial implications for protecting resources, increasing tax base, and improving environmental policies. Our analysis focuses on the three county Raleigh-Durham-Chapel Hill, North Carolina region, which has experienced rapid development and extensive aquatic ecological restoration (through the state's Ecosystem Enhancement Program [EEP]). Since restoration sites are not randomly distributed across space, we used a genetic algorithm to match parcels near restoration sites with comparable control parcels. Similar to propensity score analysis, this technique facilitates statistical comparison and isolates the effects of restoration sites on surrounding real estate values. Compared to parcels not proximate to any aquatic resources, we found that, 1) natural aquatic systems steadily and significantly increase parcel values up to 0.75 miles away, and 2) parcels < 0.5 mi from EEP restoration sites have significantly lower sale prices, while 3) parcels > 0.5 mi from EEP sites gain substantial amenity value. When we control for intervening water bodies (e.g. un-restored streams and wetlands), we find a similar inflection point whereby parcels < 0.5 mi from EEP sites exhibit lower values, and sites 0.5 – 0.75 mi away exhibit increased values. Our work points to the need for higher public visibility of aquatic ecosystem restoration programs and increased public information about their value.

1. Introduction

Regulations requiring the compensatory mitigation of streams and wetlands destroyed during development have spawned the most widespread and sophisticated ecosystem service markets in the United States (ELI 2007; Madsen et al. 2010). During this process, which has become a model for other ecosystem markets including nutrient (EPA 2010), stream buffer (EEP 2004), and endangered species habitat trading (Ruhl et al. 2005), developers are asked to avoid wetland destruction, while minimizing and compensating for unavoidable impacts. 'Compensation' in this case often means restoring alternate ecosystems – damage to one resource is 'traded' for restoration, or sometimes the creation, of another (NRC 2001). These wetland and stream trades now form aquatic ecosystem markets throughout the United States, leading to nearly $3 billion in wetland and stream restoration annually – nearly 10 fold the amount spent on U.S. Endangered Species Act habitat programs – and restore an average of over 47,000 wetland acres annually (2000-2006), and well over 240,000 linear feet of stream since record keeping began (ELI 2007; Madsen et al. 2010). This type of offset system is now being proposed to combat numerous resource impacts, from endangered species habitat (Ruhl et al. 2005) to climate change (Saeed 2004; carbon trading and offsets).

Until recently, data has been unavailable to analyze how mitigation programs actually function and what effects they have on the landscape.[1] However, new database management regimes (Martin and Brumbaugh 2011; Olson 2005) have enabled efforts to understand the landscape scale ecological and economic effects of these programs.

[1] A number of studies have documented and criticized the lack of availability and low quality of regulatory data tracking the location and behavior of aquatic ecosystem impacts and mitigation across the United States (BenDor et al. 2007; BenDor et al. 2009; Strand 2010; Urban 2009).

What effect does large-scale wetland and stream restoration, such as that occurring during wetland/stream mitigation, have on surrounding land values? Understanding the effects of aquatic ecological restoration on community real estate value could have substantial implications for local efforts to protect natural resources, increase tax bases, and develop well-designed urban-growth policies. The analogue to this is the vast literature on open space valuation, which has evaluated the intricate and complex impacts of parks and open space on land values (e.g. Brander and Koetse 2011; Tapsuwan et al. 2012).

Also important are the theoretical implications of the values attached the human-produced natural resources. Krieger (1973) challenged the environmental movement to think deeply about "What is wrong with plastic trees?". His answer, "not much," was grounded on the ideal similarities of ecological functions that could be produced from natural and artificial means; he argued that as long as artificial resources can susbtitute for natural resources lost and increase access to ameneties, then there is really nothing wrong with plastic trees. Studies are necessary to evaluate whether there is a tendency among households to value naturally occuring environmental resources more than the artificial resources created as part of the growing movement towards ecological offset policy. Unfortunately, while wetland valuation is a topic of intense debate in the urban and environmental economics literature, few studies have focused on the effects of wetland restoration (or any type of ecological restoration) on surrounding real estate values.

It is important to note that several studies have analyzed the values of human-made wetlands that were constructed for specific purposes (e.g. stormwater wetlands for flood control, or water purification wetlands). For example, Ghermandi et al. (2010) found very high values for human-made wetlands, possibly due to the fact that human-produced ecosystems are usually constructed with the specific purpose of providing services for human use and thus their value is more easily realized by surrounding populations. However, unlike Ghermandi et al.'s (2010) study, we are not examining wetlands created for human consumption; U.S. wetland regulations instead require the restoration of wetlands for a full suite of purposes, including habitat, water quality enhancement, flood control, and others that may yield less value to surrounding populations.

In order to isolate the effects of ecosystem restoration on nearby real estate values, we statistically examine spatial and temporal data on wetland and stream mitigation sites collected for the three-county Research Triangle Region of North Carolina (USA) region between 2000 and 2007. This region is particularly suitable for this analysis as it has experienced both abundant aquatic ecological restoration (ELI 2005) and rapid development (Ewing et al. 2002). We examine all ecosystem restoration sites in this region, which are comprehensively managed and planned by the North Carolina Ecosystem Enhancement Program (EEP), a state agency that plans for, purchases, and re-sells aquatic ecosystem mitigation to both state and private permitees (Dye Management Group 2007).

This article begins with a short discussion of pertinent policy background information, followed by information on our dataset and study area. Next, we discuss our analysis methods and present our results. Finally, we offer conclusions and implications for further research in this area.

2. Background

Since 1988, United States' aquatic ecosystem protection regulations have centered on achieving a goal of "no net loss" of wetland acreage and function throughout the Nation

(National Wetlands Policy Forum 1988). A substantial part of this goal is achieved through Section 404 regulations of the U.S. Clean Water Act (13 USC 1344), which protects aquatic resources by requiring permits for destruction ("impacts") to resources. These permits typically require impact avoidance, minimization, and compensation (offsets) for unavoidable impacts through ecosystem restoration (NRC 2001).

Valuation of Wetlands

Although the impact of wetlands on land values has been explored in detail by a substantial hedonic analysis and contingent valuation literature, there is substantial disagreement over precisely the types of amenity or disamenity values wetlands actually provide. For example, Boyer and Polasky (2004) reviewed literature demonstrating that property owners value proximity to wetlands in urban areas. However, survey research performed by Stevens et al. (1995) has shown that participants mostly valued wetlands in terms of their nonuse value (the monetary value that a person places on resource independent their present or future use of that resource), regardless of wetland proximity.

A number of studies have attempted to quantify the precise use and nonuse values associated with wetland benefits. Mahan et al. (2000) show that decreasing the distance to wetlands by 300 meters from an initial distance of 1.6 kilometers led increases in property value of approximately $436 (1994 dollars). However, although many of the local urban benefits of wetlands may diminish with distance (Ruhl and Salzman 2006), in rural areas, results have been more mixed; Reynolds and Regalado (2002) found the *type* of wetland largely determined whether the presence of a rural wetland positively or negatively affected land values.

Meta-analyses (Brander et al. 2006; Woodward and Wui 2001) and reviews (Boyer and Polasky 2004) suggest that while valuation techniques can be very useful within specific study areas, attempts to extrapolate findings can lead to large discrepancies in estimates. There is also substantial disagreement in the literature on whether valuation methodology affects estimated values (compare Brander et al. 2006; Woodward and Wui 2001). Socioeconomic variables such as income and population density have been shown to be particularly important in explaining estimated wetland values (Brander et al. 2006).

What effect does large-scale wetland and stream mitigation sites have on surrounding land values? The prevailing attitude of the hedonic literature appears to be that wetlands often increase land values, primarily when valued by populations that understand their ecosystem services. In a rare meta-analysis of both naturally occuring and man-made wetlands Ghermandi et al. (2010) find that wetland values increase alongside anthropogenic pressure. Using a regression model to analyze 418 observations from 170 valuation studies conducted on 186 wetland sites worldwide, the authors compile a complex set of findings, including their observation that the value of specific wetland services vary among different wetland types (similar to Reynolds and Regalado 2002). Perhaps more pertinent for our study, they find that human made wetlands create high values for biodiversity enhancement, water quality improvement, and flood control.

Based on these findings, and considering the combination of parallel domestic efforts of governments at the local, state, and federal level to enact wetland protections, we hypothesize that wetland restoration increases surrounding residential land values due to its tendancy to create amenity values (e.g. aesthetic values and high quality open space conservation, flood protection; Mitsch and Gosselink 2000) within the landscape.

This study uses a different approach than typical hedonic models to arrive at the amenity value internalized by homes surrounding EEP restoration sites. Unlike hedonic price models of naturally occuring wetlands in the landscape, the act of ecological restoration constitutes a planned, non-random action in the landscape that is likely to be associated with a variety of aspects of the landscape, including the relative type, size, and value of parcels to be restored. Therefore, we do not use a parametric model (like OLS) to account for the impact of restored wetlands, which would incur substantial bias in our estimates. Instead use a causal inference model that controls for many of the factors that affect sale prices. In the next sections, we describe our study region and the methodology that we use.

3. Data and Study Area

Our analysis focuses on the three-county region encompassing the Cities of Raleigh, Durham, and Chapel Hill, North Carolina (the 'Research Triangle;' Figure 1). This region is ideal for studying this topic, as aquatic mitgiation and urban growth are both abundant and data is readily available. Rapid urban development in the Triangle region has created a large sample of recently sold businesses and homes (collected from county governments), allowing us to isolate the effects of restoration sites on nearby real estate values.

Data used for this study consist of three primary datasets, including geo-spatial data on compensatory mitigation projects, longitudinal real estate data, and neighborhood- and county-scale data used to control for co-variates that affect residential land values throughout the region. These co-variates included school quality (proxied using mean combined SAT critical reading and mathematics scores), distance to major regional employment centers (the three major research universities[2] and the Research Triangle Park, an extensive office and lab complex; Link and Scott 2003), and crime rates.

Data on mitigation site locations was available and collected from the North Carolina Ecosystem Enhancement Program (EEP). The EEP represents a unique model in that it employs an extensive watershed planning process (BenDor and Stewart 2011; D'Ignazio et al. 2005), while acting as a non-regulatory, public intermediary that re-sells wetland and stream credits[3] for use as aquatic mitigation by both private (land developers) and public entities (historically the NC Department of Transportation (NCDOT); see Dye Management Group 2007). Although this is relatively unique institutional structure, programs across the U.S. are considering it as a model for their own mitigation programs (D'Ignazio et al. 2005; EEP 2009a).

One strong advantage of studying the EEP is that, in its capacity as a 'credit re-seller', the EEP acts as a 'clearinghouse' for mitigation credits throughout the state, facilitating data collection for several different types of mitigation mechanisms[4] for which data would ordinarily be difficult to collect. Considering that scholars studying aquatic impacts and restoration have long decried the common lack of regulatory data availability (BenDor et al. 2007; Strand 2010; Urban 2009), it is important to note that the EEP manages one of the most comprehensive databases of restoration site information in the country.

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[2]These include Duke University, North Carolina State University, and the University of North Carolina at Chapel Hill, which collectively employ over 50,000 people (2010-2011).

[3] The EEP now also has nutrient offset and riparian buffer mitigation programs as well (EEP 2004, 2009b)

[4] For example, compensation can be provided by private environmental firms ('mitigation bankers'; NRC 2001), who speculatively restore wetlands for future sale into the markets for ecosystem mitigation credits. Compensation can also be provided by governments, who typically run 'in-lieu fee' programs, which collect and pool fees for aquatic impacts to fund future restoration projects (Wilkinson 2008).

While the EEP institutional and planning models appear to be fundamentally unique, it is first important to note that many of the EEP's restoration sites were purchased directly from private mitigation bankers during our study period (~35%; and ~53% after the study period) through a process known as 'full-delivery' (Dye Management Group 2007), thereby mimicking the restoration site patterns seen in other parts of the US. Under full delivery, mitigation bankers actually purchase and construct restoration sites in watersheds where the EEP has requested that restoration site be constructed, and then sell those restoration projects to the EEP, which then re-sells those restoration credits to credit consumers (private developers or the NCDOT). Recent work (Keating et al. 1997) has outlined the logic underlying mitigation site valuation; for example, Cragg et al. (2011, Pg. 129) note that:

> "[I]f the highest and best use of a property is mitigation, a mitigation banker will be purchasing land at the same price as someone seeking to do their own off-site mitigation. This will also be the price paid in an arm's-length sale between a knowledgeable profit-maximizing seller and an environmentally motivated buyer seeking to recover wetlands."

As a result, it is important to point out that the portion of the EEP's sites that are obtained using methods similar to mitigation banking are therefore unlikely to be skewed by some sort of specialized, state-mandated pricing structure that would create a situation where the probability of restoration is entirely a result of land values. This is important, since we will need to assume, for our model, that treatment observations were not chosen based on land values themselves. While it has been observed that wetland restoration sites in extremely costly areas could suffer extreme skewing in terms of how they are located,[5] there is no evidence that this region suffers from this dynamic.

In thinking about whether or not the selection of restoration sites themselves can be a function of land values, it is also important to note that most restoration work required under the U.S. Clean Water Act (in NC and elsewhere) is wetland 'restoration' and 'enhancement,' both processes defined by the EEP (Dye Management Group 2007) that involve taking current wetlands and improving their functional characteristics. This contrasts with the type of wetland creation documented in Ghermandi et al. (2010), whereby wetlands are created out of other land uses.[6] This means that the restoration sites in our study are typically either current or formerly drained wetlands (hydric soils), and therefore not likely to be situated on land with the same range of values as other areas.

Geospatial data from the EEP contained creation date and location information for stream and wetland mitigation sites throughout the state (*N=539).* Within our study area, 41 restoration sites were identified on 126 parcels. The location of these sites was verified using publicly available site plans (EEP 2011), and through confirmation with EEP personnel. Parcels containing restoration sites can be seen in Figure 1.

[Insert Figure 1 and Table 1 about here]

The locations and typography of aquatic ecosystems were taken from the US Fish and Wildlife Service's National Wetlands Inventory (NWI; Tiner 1997). Approximately 65

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[5] For example, see BenDor et al.'s (2007) discussion of the impact of high land values and low land availability on the mitigation market in the Lake Michigan watershed (Gold Coast region) of the Chicago District of the Army Corps of Engineers.

[6] Wetland creation usually require the acquisition of non-wetland land uses, which are then turned into wetlands, thereby almost certainly creating a decline in value for the restoration site itself (as options for more profitable development into alternative uses are eliminated). Regulators usually prioritize Wetland creation just above preservation, and well below wetland restoration and enhancement (Corps and EPA 1995).

percent of the region's wetland area is located in Wake County, while Orange County accounts for only 9 percent (Table 1). Large portions of the wetlands in the region are fresh water forested/shrub wetlands, although a significant portion of the wetlands in Orange county are freshwater ponds (~46 percent). The NWI data was used to determine parcels proximate (defined in the methodology section) to lakes and ponds, streams, and all other types of wetlands (primarily palustrine wetlands; analysis include only wetlands > 2 ac [~0.81 ha]).

[Insert Table 2 about here]

Geo-spatial parcel, home sale, and land characteristic data used to control for co-variates that affect residential land values throughout the region were obtained from the three study area county governments (see full variable list in Table 2). Of the 481,433 parcels in the three county region, 73.5 percent are residential single family parcels. Because of obvious errors in recording the data, we imposed resonable bounds on the parcel attributes. For example, we selected parcels that have house of size between 300 and 10,000 sq.ft (28 and 929 m^2). The parcel size was restricted between 0.01 acres and 10 acres (0.004 and 4.05 ha). To exclude non-arms length transactions, we eliminated sales that were less than 10,000 USD. To exclude very high end houses that may include lake fronts and other ameneties, we limited our sample to sales that less than $2 million USD. Given that we are limiting our study to residential land value impacts only, this data contained, in total, information on 124,514 home sales during our 2000-2007 study period, an average of 15,564 home sales each year in the three county region. Unfortunately, available data did not include information on repeat sales that would have allowed us to create a 'difference in difference' estimator to study the effects of creation of new wetlands.[7] The dataset did, however, include information on the last sale date and the sale price.

[Insert Figure 2 about here]

Data on school assignment zones (parcels that contribute students to certain high schools) were obtained from counties (Wake County's school assignment system is substantially more complex since students are not automatically assigned to their nearest school). Data on school quality was obtained from the North Carolina Department of Public Instruction (http://www.ncschoolreportcards.com) and is represented simply by recent SAT scores for each district (Figure 2).

Crime data were obtained from all local counties and municipalities, and consisted of data on eight serious crimes (major violent and property crimes) known as Part I index crimes (Poggio et al. 1985). Obtaining only Part I crimes for Orange County was not possible, so we collected all crime data (Part I and Part II crimes). Addresses where crimes occurred were then geo-coded to determine their map location using a script developed for the MapQuest® application program interface (API). This method was chosen instead of the standard geocoding using TIGER files (Ratcliffe 2001) because of poor quality of address information in the crime files and non exhaustive listing of street addresses in TIGER files. Where appropriate, TIGER files and Google Maps® were used to supplement the poor matches from the MapQuest®. In total, ~95 percent of the reported crimes were geocoded and then aggregated at the census block level and crime rates were re-attached to parcel data as 'neighborhood' crime rates.

[7] If data were available allowing us to fully implement a quasi-experimental study design, the value of the treatment group parcels before and after wetland restoration could be compared to the value of the control group before and after restoration, thereby allowing us to explore the difference in land value differences due to restoration ('difference in difference').

Similarly, the road distances from each parcel to major employment centers (three universities and RTP) were calculated using MAPQuest API. The parcel centeroids were passed to the MAPQuest servers as origins and along with the four destinations. The resulting xml file was parsed to extract the shortest driving distance to each of the four destinations from each parcel.[8] These distance were summed up to construct an aggregate accessibility metric to the major employment centers in the region. Therefore, the parcels that are centrally located to all the four employment centers have lower values and the parcels that are not, have higher values. While this is a crude metric, this effectively captures the polycentricity of the region and does not use euclidean distances, unlike the approach taken by many hedonic analysis of amenity value of wetlands (Mahan et al. 2000).

We chose these school, crime, and parcel-characteristic variables not only because they are typically important in the literature (Clark and Herrin 2000), but also because they also form a parsimonious set of variables that explain nearly 70% of the variation of sale prices during our study time period (2000 – 2007; using a simple OLS regression, $R^2 = 0.69$ and all variables are significant ($p < 0.05$)). As can be expected, our data demonstrate that home sale prices are negatively affected by distance and crime, and postively affected by school quality, house size and site (lot) area. Home prices in Wake and Orange Counties are higher than in Durham County, which has only recently begun to experience redevelopment. While this simple regression analysis is not discussed in the methodology described below, this intermediate data collection and methodological step suggests that our study variables play an important role in explaining variation in housing sale prices.

[8] The region has very little public transit, though this approach can be adapted in areas with high quality transit.

4. Methodology

Because property values of houses incorporate many elements of the attributes of the house, as well as the location, the impacts of EEP sites on home sale prices are difficult to determine. Simple averages of sale prices of parcels near and far from the EEP sites are misleading because the estimates are both biased and inconsistent. A standard technique (hedonic regression) to determine the sale price effects of EEP sites would to regress the sale prices on various attributes of the house and the site, while including a dummy variable for those sites that are near EEP sites and are sold after the EEP construction.[9] These kinds of hedonic models rely on a number of assumptions, including the linear parameterization, normality and independence of the errors.

However, a number of technical problems underlie the use of a hedonic regression analysis for our purposes, including problematic assumptions about linear parameterization and the distributional equality of the covariates for treatment and control subsamples. For example, including a dummy variable to denote proximity of parcels to nearby aquatic features in hedonic models can be problematic because of selection bias and distributional differences among parcels near and not near wetlands. If the distributional differences are large, the projections for treatment and controls are essentially out-of-sample projections and therefore sensitive to functional specification.

[9] As an additional test, we ran a standard OLS regression model of the data, which suggested that the effect of natural wetlands is significant compared to the other parcels (~\$2800; $P<0.05$). On the other hand, EEP restoration does not seem to have any statistically significant effect compared to other parcels (positive, but not significant) or compared to wetlands (negative, but not significant). While the R^2 of these models are relatively high (~0.65), they suffer from such serious violations of basic OLS assumptions (see Kennedy 2003) that they are not worth elaborating on here. However, the OLS models do serve to reinforce the results of this study that EEP wetlands have complex effects on nearby house prices.

In addition to these technical issues, hedonic price models of naturally occuring wetlands in the landscape are problematic for our purposes since they assume no endogeneity between the location of restoration sites and land values themselves. The act of ecological restoration constitutes a planned, non-random action in the landscape that is likely to be associated with a variety of aspects of the landscape, including the relative type, size, and value of parcels to be restored. Hedonic regression models would not be able to control for the fact that restoration sites are often located as a function of land values and other important ecological, hydrologic, or other landscape factors.

To avoid these problems, we take a non-parametric approach.[10] We use Rubin's (1974) causal model to infer the effect of the restored sites on parcel values. The main advantage of this approach is that it simulates an experimental design of causal inference, where treatments and controls can be adequately selected and the functional form of the covariates need not be selected *a priori.* Although we cannot create an experiment randomly distributing EEP sites around the landscape, we can simulate this experiment using available data; if we select parcels that are similar in most respects, except for whether or not they belong to the treatment or the control group (nearby EEP restoration sites or not), then direct comparisons can be made that simulate a controlled experiment. Although this is not possible in typical observational studies, the key idea is to recast the control-treatment matching problem as a "missing value problem," (explained below; Rubin 1974), which can be solved using matching techniques.

Creating a useful matching estimator

[10] An interesting future area of research could statistically compare hedonic modeling and matching estimator methodologies.

Let Y_i^t be the price of a house on parcel i near an EEP restoration site and observed after ecological restoration has taken place (treatment).[11] Let Y_i^c be the price of a house on parcel *i* that does not meet these criteria (control). The treatment effect of creating a new restoration site for parcel *i* is $Y_i^t - Y_i^c$, and the average treatment effect (ATE) is $E(Y_i^t - Y_i^c)$, where E is the expectation operator. However, both Y_i^t and Y_i^c are never observed simultaneously; only one Y_i^{obs} is observed, and therefore the other is missing. In observational studies, covariates X are assumed to be the only source of omitted variable bias. Under strong ignorability, i.e. $0 < \Pr(T = 1|X) < 1$, and when observed sale prices are independent of the treatment assignment conditioned on *X,* where *X* is a set of covariates, then ATE is:

$$E(Y_i^t - Y_i^c) = E\left(E\left(Y_i^{obs}\middle|X, T = 1\right) - E\left(Y_i^{obs}\middle|X, T = 0\right)\right)$$

where T is the treatment status. The strong ignorabilty condition implies that the probability of selection into the treatment is not perfectly predicted by the covariates. As we discussed earlier, all evidence suggests that the EEP chooses ecological restoration sites based entirely on the ecological 'uplift' (highlight ecological utility of wetland restoration; (Perrow and Davy 2002) of a given site, rather than simply restoring in areas where land values are low. Furthermore, because restoration sites are nearly always pre-existing wetlands (wetland 'creation' is given very low value under wetland mitigation generally; NRC 2001), their land prices are largely independent of the factors that affect housing prices.

[11] It is of mild concern that prices are only observable after sale and not observable directly upon treatment. However, sale prices presumably encompass the amenity value of the wetland long after treatment. To control for macro-economic variations in prices, we match treatments and controls within the each year of sale.

Conditioning on X eliminates bias in a perfectly balanced set up (i.e. distribution of X is the same between treatment and control groups). Note that a linearity assumption is not required here, unlike the hedonic regression approach. Matching estimators are fairly common practice, though have not been used to study the effect of wetlands before (Abadie and Imbens 2006; Heckman et al. 1998; Rosenbaum and Rubin 1985).

Conditioning on X requires finding the closest observation of the treatments and controls. Matching estimators are most accurate if we can match the treatments and controls exactly on X. However, in most planning applications, the covariates are continuous and it becomes impractical to perform exact matches. In such cases, propensity score analysis is often used (Lynch et al. 2007; McMillen and McDonald 2002). Propensity scores can be thought of as the probability that parcels are assigned to a treatment group, conditioned on a series of covariates X. Parcels are then matched to one another based on the closeness of their propensity scores, after which standard tests of differences of means are conducted to determine if there is an inter-group difference in the variable of interest. Matching based on this approach relies on correctly specifying the propensity score model, which is usually unknown.

Instead, we can also try and minimize the distance between the covariates (in our case, the parcel and neighborhood attributes) directly. One approach for doing this is to specify an appropriate distance metric for the multivariate data. One such distance metric is known as *Mahalanobis distance,* and is defined between covariate vectors of parcels i and j, $X_i$and X_j as:

$$\left[(X_i--X_j)'S^{-1}(X_i--X_j)\right]^{\frac{1}{2}}$$

where S is the covariance matrix of X. One can find the closest match by finding the control parcels that have the smallest covariate distance to each of the treatment parcels, and vice versa. Methods using this metric have equal percent bias reduction (EPBR) only when covariates have ellipsoidal distributions (Rubin and Thomas 1996).[12] This Mahalanobis distance can be modified by introducing a positive, definite weight matrix *W*, whose non-diagonal elements are zero, thereby recasting the distance metric as Sekhon (2011) suggests:

$$\left[(X_i - X_j)'(S^{-\frac{1}{2}})'W(S^{-\frac{1}{2}})(X_i - X_j)\right]^{\frac{1}{2}}$$

where $S^{-\frac{1}{2}}$ is a Cholesky decomposition of S (the covariance matrix of X). If the weight matrix W corresponds to the identity matrix, then this equation is similar to Mahalanobis distance matching.

This weight matrix W can either be specified or derived from the data. Sekhon and Mebane (1998) use a genetic algorithm to find the optimal weight matrix W that minimizes the differences between the distributions of control and treatment groups. The key innovation has been to find the optimal weight matrix W that maximizes overall covariate balance without specifying it *a priori* (Diamond and Sekhon In Press; Mebane and Sekhon 2011; Sekhon 2011). This algorithm is implemented in a statistical software environment *R* (R. Development Core Team 2009) in packages "*matching*" and "*rgenound*" (Mebane and Sekhon 2011). While any definition of distributional differences can be specified, the default in this algorithm is to minimize, "the overall imbalance by minimizing the largest

[12] EPBR may not always be desired because covariate imbalances in one variable may significantly affect the responses in the case of non-linear relationships between outcome and covariates. So for example, if we know that Y is related to X^3 and Z, then reducing the bias in X is more important than reducing the bias in Z. See Sekhon (2011) for more discussion.

individual discrepancy, based on p-values from KS [Kolmogorov-Smirnov] tests and paired t-tests for all variables that are being matched on(Diamond and Sekhon In Press, p. 7)."

This algorithm initializes a fixed population size of weight matrices (e.g. 100 in this case) and calculates the matched samples for each of the matrices. The loss function is evaluated for each matched sample, and the matrix with the minimum loss is chosen and improved in the next iteration through mutations and crossovers. The algorithm stops when no further improvement in the covariate balance is observed. If X contains both the propensity score and the attributes, the genetic algorithm finds the 'optimal' weight matrix that either matches based only propensity score or only on Mahalanobis distance or a weighted combination of both. If X is just a propensity score, or the optimal W is a zero matrix (except for the element corresponding to the propensity score), then the method simply becomes a propensity score matching technique. If X is just the covariates and the W is the identity matrix, then the technique is the same as matching on Mahalanobis distance. In this paper, we use both the attributes of parcels and the propensity score as X.

Genetic algorithms are computationally intensive, particularly when sample sizes are large, as is the case in this study. Fortunately, iterations are parallelizable, facilitating the use of computer clusters to speed up computation.[13] Because no model structure is specified, the method is non-parametric, although when propensity scores are included in X the method is semi-parametric.

In this paper, we construct four proximity-based sets of the same three causal models to understand the relationships between matched parcels proximate to EEP restoration sites and other parcels in the landscape. In the first model, we consider

[13] Two such 50 node Linux clusters were used in this study. Estimations took between 20 min and 6 hours, depending on the sample size and the number of covariates.

treatment parcels to be homes that are proximate to NWI wetlands, while control parcels include all other properties. In the second model, we refocus the model so that 'treatment' parcels are taken to be homes that are proximate to EEP sites and are sold after the EEP site is constructed. All parcels that are not proximate to any type of aquatic ecosystem (wetlands, streams, and lakes/ponds) are considered to be the control parcels.

Finally, in the third model, parcels proximate to EEP sites (and sold after EEP site construction) are again considered to be treatment parcels, while other residential parcels are considered controls. However, unlike our first model, this time we additionally match parcels based on whether they are proximate to different kinds of aquatic ecosystems, such as streams, lakes/ponds, and wetlands. This statistically controls for any intervening effects of non-EEP related water bodies that may affect land values in spurious ways. In each model, care was taken to match the treatment and control groups within the year of sale, so that macro-economic effects of the recent housing bubble do not affect results.[14]

Unlike standard regression models, which can use distance to wetland as a continuous variable, matching estimators rely on groupings of parcels into treatment and control sets, thereby requiring hard proximity cutoffs delineating treatment (referring to all properties within a certain distance radius) and control parcels relative to EEP sites.[15] We consider four different proximity distances, including 0.125 (~ 0.2 km), 0.25 (~ 0.4 km), 0.5 (~0.8 km), and 0.75 mile (~ 1.2 km) radius; a parcel is considered proximate to a stream if the streams abuts or crosses a property (Glober 2008).

[14] The addition of aquatic feature matching variables (dummy variables for ponds/lakes, streams, and wetlands) geometrically compounds segmentation of the dataset by year (8 group segments necessary perform the intra-year matching that eliminates sale price variation due to macro-economic influences).
[15] Additional research is necessary to compare the effects of this distance cutoff; experimenting with different distances requires the creation of a completely new set of treatment and control parcels, which is outside the scope of this study.

5. Analysis Results

In general the balance is improved with matching for many variables, though the effect is most noticeable in analyses that have large samples. As an example using the ¼ mi (~0.4 km) proximity case, Figure 3 shows the empirical QQ plots of each of the covariates in the treatment and control groups of each of our three models. These plots help us demonstrate the extent to distributional differences in covariates before and after matching. Significant improvement can be seen in the balance of age of the structure and parcel size (QQ plots are more linear after matching). However, while neighborhood variables such as crime rates and average SAT scores show improvement in distributional discrepancy, they remain in-completely balanced. This is expected since SAT scores and crime rates are neighborhood variables. Houses belonging to a neighborhood receive the same value and there are a limited number of school districts and census block groups in the region to which parcels can be assigned.

[Insert Figure 3 about here]

The presence of an aquatic feature (non-EEP) in the landscape has a statistically significant, modestly positive effect on surrounding home sale prices (~$3,100 USD; $p < 0.001$) compared to parcels with no proximate wetland present (see Table 3). This effect remains stable (within a range of ~$4,000) and significant between all four proximity bands (0.125 – 0.75 mi).

[Insert Table 3 about here]

The presence of an EEP restoration site had more complex impacts on proximate land values (Models 2 and 3; all impacts are significant to $p<0.000001$). At the smallest distance band (0.125 mi; ~0.2 km), EEP sites affected surrounding property values negatively (-$15,536 USD), when compared to parcels not proximate to aquatic features (Model 2). This effect declines substantially as we increase the proximity buffer to 0.25 mi, whereby EEP sites lower values an average of $9,343.2 USD. However, when we extend the proximity distances to 0.5 mi and 0.75 mi, EEP sites appear to induce strong *positive* effects on surrounding land values, increasing prices by $4,430.5 and $42,315, respectively.

Finally, when we control for the presence of other water bodies nearby (Model 3), property values within 0.125 mi of EEP restoration sites are reduced by -$12,336, which shrinks to -$8,510 when the proximity distance grows to 0.25 mi. In a similar manner to model 2, when the proximity distance grows to 0.5 mi or 0.75 mi, EEP sites are observed to increase property values by $11,780 and $8,345.7, respectively. This effect appears to stabilize between 0.5 and 0.75 mi buffers more than model 2.

6. Discussion and Conclusions

The three models that we evaluated in this study reflect three different statistical analyses that each partially explain the how EEP restoration sites affect surrounding land values. In essence, these models statistically isolate, in a quasi-experimental manner, 1) the impacts of restoration sites on surrounding land values as controlled by parcels that are not proximate to wetlands, 2) the impacts of wetlands (generally) on surrounding land values, as controlled by parcels that are not proximate to wetlands, and finally, 3) the impacts of EEP sites on surrounding land values, as controlled by parcels that are themselves near aquatic features.

Our finding that non-EEP wetlands significantly increase property values by approximately $3,100 is directly in line with much of the hedonic literature on wetlands, such Mahan et al. (2000). The small premium that is generated for parcels proximate to non-EEP wetlands in the region may be the result of proximity to lake fronts (many wetlands in the region surround larger lake areas [lacustrine wetlands]). While water bodies have long been known to provide high amenity values (David 1968), remaining wetlands in the region may also be of fairly high value (not necessarily quality), and act as informal park areas with accompanying aesthetic and recreational opportunities (birding, trails, etc.).

EEP sites decrease values in very close proximity

Our finding that EEP sites generate a relatively strong disamenity value at close distances (< 0.5 mi) forces us to consider three possible explanations: 1) wetland and stream modification can induce enormous temporary aesthetic damage to restoration sites, damaging aesthetic values and creating perceptions of restoration sites as 'damaged goods,' (discussed further in the next section)[16], 2) the public has limited knowledge of EEP restoration projects, and 3) not enough time has lapsed for the amenity value of EEP restoration efforts to internalize into surrounding property values. We discuss the two latter explanations below.

Hedonic literature points out that the land value manifestation of environmental values is often tied to public awareness and understanding of specific environmental amenities (Boyer and Polasky 2004). Although the EEP has received numerous state and national awards for its restoration efforts (EEP 2009a), it is not clear whether the buyers of homes proximate to EEP sites are even aware of the agency or the sites.

This public relations issue may be most clearly manifested in Triangle Land Conservancy's (2002) "State of Open Space" plan, an effort to catalogue all protected green

[16] This spatial proximity may also resemble disamenities perceived for naturally occuring wetlands in rural areas by Reynolds and Regalado (2002).

infrastructure (ecological and recreational space) within the region. Nowhere in the plan do EEP sites register as protected open space, even though long-term protective easements are placed on all EEP projects. Furthermore, additional plans and catalogues of open space in the region rarely include EEP sites. One reason for this may be that, until recent web-mapping overhauls were made in 2011 by the agency, locating comprehensive data on EEP restoration site locations was very difficult.

The third potential explanation for our findings relates to the extent to which the amenity value of EEP sites has been internalized into surrounding property values. Although perfect markets rely on costless information search and transfer, it is well known that property markets are far from perfect (Levitt and Syverson 2008). It is possible that, given low public awareness of the EEP sites, infromation about the amenity value has not yet been captured in sale prices soon after the construction of the EEP sites. On average, home sale dates were 3.4, 3.8 and 4.4 years after the EEP site construction date in Orange, Durham and Wake Counties, respectively. This may not be enough time for the home buyers to internalize the amenity value into property value. Further, long-term studies are required to understand any evolution of restoration site effects on land values.

Value Effects as a Function of Distance

We hypothesize that the inflection between increases and decreases in EEP land value effects may be the result of restoration site construction processes that create strong disamenities for closely surrounding residents, but create improved landscape ecological functions for residents at a larger landscale scale (beyond the 0.5 mile radius). While the distance band around EEP sites where land values decrease appears to be very narrow

(<0.5 mi), one explanation can be found in observing the history of EEP restoration construction.

Throughout the agency's history, the public perception of low ecological quality of EEP stream and wetland projects have been problematic. Although a well-publicized report by Penrose (2006) first brought the questionable biodiversity value of EEP stream restoration sites into the spotlight, two earlier studies (prior to our study period) by the Federal highway Administration (FHWA 1995) and Pfeifer and Kaiser (1995) found major mitigation failures in North Carolina. The FHWA (1995) studied mitigation projects between 1986 and 1992, finding that of the five sites with documentation available, only one (20%) successfully produced the targeted wetland type. The larger study by Pfeifer and Kaiser (1995) evaluated 24 mitigation sites (1991 - 1993), of which only 10 (42%) were considered to be "successful." These problems may have begun to change already; in 2010, the NC Department of Natural Resources (Hill et al. 2010) released an analysis of 98 wetland and 129 stream sites, reporting statewide mitigation success rates had risen drammatically to 74.5 and 75.0 percent, respectively.

When we extend the proximity distance to more than 0.5 mi, EEP sites appear to strongly increase land values. These dynamics more closely correspond to those observed by Ghermandi et al. (2010), whereby restoration sites increased land values because of their biodiversity enhancement, water quality improvement, and flood control benefits. This finding is encouraging, as it appears that to suggest that restoration can directly increase the amenity value of resources at a local scale.

Given the inflection point that we have observed, the question that remains: how does ecological success in restoration, which appears to have risen dramatically since the

1990s, actually translate into amenity value perceived by local residents (and internalized into surrounding land values)? Although data to answer this question are improving, the U.S. housing and financial collapse makes studying 2008 and subsequent years difficult, as macro-economic price signals are likely to dominate throughout the region.

Study Limitations

Like most studies, our methodology was partly determined by the limited data available on several different fronts. For example, we did not discriminate between different sizes and types of restoration (e.g. quality, streams vs. wetlands, etc.), which would necessitate many more restoration sites out of which to form groups of treatment parcels. Additionally, despite our efforts at optimization, balance between treatment and control groups is not completely achieved, which limits the usefulness of the results Furthermore, given that repeat sales data were unavailable, we were not able to use multiple sale time points to construct treatment and control parcel samples that would have allowed us to perform a difference-in-difference analysis. Using this method, we would have been able to more accurately capture the effects of new EEP restoration sites. We leave this type of analysis for future research, and recommend the collection and use of data on multiple sales over time.

We must recognize that restoration of aquatic ecosystems can generate multiple types of spillover effects, many of which cannot be untangled. In our case, the two primary coupled effects include 1) the effect of aquatic ecosystem restoration itself, and 2) the effect of the change in ownership status, which may occur when restoration is performed on private land. This latter effect functions as a land re-assignment from undeveloped open space to a permanently preserved area, which could have a strong land price premium attached to it. While it is difficult to distinguish these co-effects in this type of study, a future study could compare programs like the EEP's with other restoration techniques that do not prompt an immediate change in land ownership.17

This is the first study to use matching estimators to understand the land value effects of ecological restoration and our work points at several future research directions. The caveats that we note in our modeling methodology point to the need for future research into this area. For example, the effect of ecological restoration on nearby housing values could change over time and thus be dependent on the length of time between restoration and the sale of the house. We might even expect that the land value effects of restoration could invert over time; that is, effects that are initially negative when vegetation is still establishing (which could last for years, if not decades; e.g. BenDor 2009) could turn into positive effects after the site is well-established and substantial aesthetic and wildlife services emerge.[18]

Furthermore, it should be noted that this study looks at the fairly narrow question of whether proxmity to aquatic restoration affects sale prices. The wider benefits of creating new aquatic ecosystems have been, and continue to be, the purview of extensive research in ecological science and not within the scope of this work. The potential positive or negative externalities imposed on the neighbours of these sites should be balanced against the larger public interest.

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[17] It's worth pointing out, however, that ownership changes occur regularly during aquatic ecosystem mitigation around the country, where restoration sites (or easements for those sites) have commonly been deeded to non-profits, local governments, park districts, or state property offices for long term management.

[18] Reflecting these complex external effects, Cragg et al. (2011, Pg. 150) remark on the intracacy of valuing restoration sites themselves, noting that "the valuation of land with wetland potential requires a thorough analysis of the influences on wetland supply and demand for the region in which the land is located. More specifically, the valuation of lands with wetland potential must explicitly incorporate the influence of federal and regional policy, paying particular consideration to how mitigation credits are determined within the region."

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Tables

Table 1: NWI wetland area in the three-county region (in hectares)

	Freshwater Emergent Wetland	Freshwater Forested/ Shrub Wetland	Freshwater Pond	Lake	Riverine	Total
Durham	300.7	3,390.9	477.1	461.7	58.7	4,689.1
Orange	64.3	535.0	719.1	182.1	62.7	1,563.7
Wake	234.7	7,437.7	2,230.2	1,819.1	99.1	11,822.9

Table 2: Summary Statistics for parcel and neighborhood characteristics (n = 85,734)

Source	Variable	Min	1st Q	Median	Mean	3rd Q	Max
County GIS data	Sale Price	10,500	205,381	170,000	205,381	248,000	1,950,000
	House size (m^2)	33.4	124.4	160.0	177.6	215.1	921.5
	Site (lot) Area (ha)	0.004	0.073	0.117	0.214	0.020	4.046
	House Age	2	7	16	22.4	32	106
Sheriff and police crime data	Annual crime rate (crimes / pop.)	0	0	0.006	0.0166	0.02	0.2
School districts	Average SAT score	800	1012	1058	1045	1094	1218
GIS analysis using local road data	Cumulative Distance (km)	62.49	105.62	105.62	133.50	158.76	313.16

Table 3: Differences in residential sale prices between treatments and controls within four different proximity rings (0.125 mile, 0.25 mile, 0.5 mile, and 0.75 mile)

		Model 1	Model 2	Model 3
Treatment		Near non-EEP wetland	Near EEP site and sale after EEP restoration	Near EEP site and sale after EEP restoration
Control		Not proximate to any wetlands	Not proximate to any wetlands	Not near EEP sites /or near EEP sites but sold before EEP site construction
Data Segmentation:		Matched within year of sale (8 groups)	Matched within year of sale (8 groups)	Matched within year of sale and proximity to different types of natural wetlands (32 groups)
0.125 mi radius (~0.2 km)	Estimate	3,111.6	-15,536	-12,336
	Std. error	329.24	509.02	487.11
	t-statistic	9.4511	-30.522	-25.325
	p-value	< 2.22e-16	< 2.22e-16	< 2.22e-16
	Sample size	86,663	68,939	84,204
	Parcels in treatment	17,724	668	838
0.25 mi radius (~0.4 km)	Estimate	2,513.6	-9,343.2	-8,510
	Std. error	327.59	542.11	412.53
	t-statistic	7.67	-17.24	-20.63
	p-value	<1.70E-14	< 2.22e-16	< 2.22e-16
	Sample size	86,663	50,647	82,526
	Parcels in treatment	36,016	1,116	1,757
0.5 mi radius (~0.8 km)	Estimate	6,371.6	4,430.5	11,780
	Std. error	365.98	850.42	425.42
	t-statistic	17.41	5.2098	27.692
	p-value	< 2.22e-16	<1.90E-07	< 2.22e-16
	Sample size	86,663	22,820	85,867
	Parcels in treatment	63,843	1,349	3,674
0.75 mi radius (~1.2 km)	Estimate	2,778.3	42,315	8,345.7
	Std. error	398.94	1,839	432.39
	t-statistic	6.9641	23.01	19.301
	p-value	<3.29E-12	< 2.22e-16	< 2.22e-16
	Sample size	86,663	8,521	85,866
	Parcels in treatment	78,142	1,003	5,726

Figure Captions

Figure 1: Triangle Region, North Carolina Study Area with Aquatic Ecosystem Restoration Sites

Figure 2: The distribution of neighborhood quality variables represented by school quality and average annual crime rate

Figure 3: Empirical QQ plots of covariates before and after matching for various estimates (example using ¼ mi [~0.4 km] proximity distance)