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Identifying the Impacts of Critical Habitat Designation on Land Cover Change

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RESOURCES FOR THE FUTURE

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Abstract

The US Endangered Species Act (ESA) regulates what landowners and land managers can do on lands occupied by listed species. The act does this in part through the designation of habitat areas considered critical to the recovery of listed species. Critics have argued that the designation of critical habitat (CH) has substantial economic impacts on landowners above and beyond the costs associated with listing in general. Here we examine the effects of CH designation on land cover change from 1992 to 2011 in areas subject to ESA regulations. We find that, on average, the rate of change in developed land (urban and residential) and agricultural land is not significantly affected by CH designation. In addition, our estimate of the effects of CH designation is not strongly correlated with the costs of CH as predicted by economic analyses published in the *Federal Register*. While CH designation, on average, does not affect the overall rates of land cover change, CH designation does appear to modify the impact of land cover change drivers. Generally, land prices had more impact (statistically) on land cover decisions within CH areas than in areas subject to ESA regulations but with no CH designation. Land cover decisions in these latter areas tended to be driven more by clustering and land availability concerns. These trends suggest that CH designation has increased landowner uncertainty and that conversion to developed and agricultural use in CH areas, on average, requires a return premium. Overall, however, this different reaction to land prices in and outside of CH areas has not been strong enough to differentiate the average rates of developed or agricultural land change in CH areas versus areas subject to ESA regulations but with no CH designation.

Key Words: critical habitat, opportunity cost, land cover change, matching analysis

JEL Classification Numbers: Q24, Q28, Q57

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1. Introduction

The US Endangered Species Act (ESA), like any land-based regulation, can create costs by limiting economic activity that would have otherwise occurred on an unregulated landscape. Restrictions on *land management* are one category of costs created by the ESA. For example, a forester on US Forest Service land could be prevented from adopting a more intensive method of logging if the more intensive method is deemed harmful to a listed species that occupies the area; a farmer could be prevented from converting his agricultural land from pasture to more lucrative cropland if the act's regulators deem the pasture as listed species habitat; or the rate and timing of water withdrawals from a river could be regulated if a listed species occupies the waterway.

The ESA may also prevent *land use and cover change* (hereafter shortened to "land cover change"). In this case, a farmer may not be able to sell land to a housing developer if the act's regulators find that development would threaten the existence of a listed species. The clearing of trees to build a public road could also be prevented if the act's regulators decide that this action could destroy a listed species or its habitat or otherwise jeopardize the continued existence of the species.

Unlike with other well-known environmental regulations, there are no comprehensive estimates of the opportunity costs created by the ESA. While costs for some critical habitat (CH) designations and specific actions recommended in species recovery plans have been estimated,

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such cost estimates are sporadic and inconsistent. An accurate measurement of *all* ESA-generated costs on the landscape requires a land cover and land management counterfactual—a model of the US landscape over time without the ESA. Whereas assessors of the Clean Air Act Amendments and other US environmental regulations have built credible counterfactual models of US economies without the regulation in question (e.g., Chan et al. 2012), such a comprehensive counterfactual for the ESA is not possible when range maps and habitat associations for many listed species are imprecise and incomplete. Identifying where and how the ESA has affected decisionmaking by both government officials and private landowners is difficult when regulated space and jurisdiction are imprecisely known. Such spatial impreciseness does not affect the CH portion of the act, however. Each CH designation—an area of habitat deemed to be essential or critical to a listed species' conservation—is precisely delineated by a map published in the *Federal Register*.[1]

Precisely delineated CH areas have the potential to affect human behavior on the landscape more than any other part of the ESA because they, unlike many other portions of the act, specifically indicate where ESA regulations must matter. Consider the argument by the US Fish and Wildlife Service (FWS) that CH is unnecessary because its related regulations duplicate sections of the act that prevent land use and land management decisions on private and public land that would result in a "taking" of a listed species or put a listed species in jeopardy (Sections 7 and 9 of the act).[2] However, the impreciseness of listed range space and affected habitats undoubtedly leads to cases where ESA regulations are unenforced because of ignorance and uncertainty, with landowners and public land managers unaware of any potential restrictions on their choices. Such uncertainty over regulated space is not possible in CH areas. Therefore, we should see significantly more regulatory and regulation-affected landowner behavior within CH areas than without. The specificity of the CH maps also provides nongovernmental organizations concerned with threatened species survival a guide to cost-effective investment. According to conservation scientists, these are the areas of the US landscape most vital to species conservation, and therefore habitat in CH areas should attract an extraordinary amount of attention from conservation organizations.

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[1] As one federal court put it, "Critical Habitat is the area 'essential' for 'conservation' of listed species. Conservation means more than survival; it means recovery" (Suckling and Taylor 2005).

[2] "Taking" has been interpreted by US courts to include the killing, harming, harassing, pursuing, or removing of the species from the wild on private and public land.

Therefore, our hypothesis is that, on average, land development rates in areas designated as CHs were lower from 1992 to 2011 than in similar areas in listed range space but without CH treatment.[3] In other words, we postulate that the CH rule creates land cover change opportunity costs above and beyond the costs associated just with an ESA listing. This expectation is based on the extraordinary attention that CH designation (and their mapped representation) should bring to these specific portions of listed species' ranges. We are limited to examining the impact of CH on land cover change opportunity costs because the maps we use in this analysis provide only land cover information and not management information.

We do not expect the impact of CH designation to be same everywhere across the US landscape. Landowner, land manager, regulatory agency, and conservation organization reaction to CH designation will be a function of economic and other landscape features found in the CH. For example, a CH that covers land for which developers are willing to pay a premium is likely to experience greater development after CH treatment than a CH that covers land with little commercial value. Further, regulatory agencies may be less active in CHs with high land values in order to avoid generating large opportunity costs or facing too much political pressure, while conservation agencies may be less active in CHs with high land values to avoid using too much of their land conservation budget. Therefore, after estimating the average treatment effect of CH designation on land cover change rates, we use econometric techniques to explain what drives land cover outcomes in CH areas.

Finally, we relate our treatment effects to CH cost predictions published in the economic analysis section of *Federal Register* notices designating CH. The approach taken to estimating these costs has varied over the years, so we attempt to distinguish costs that are attributed to CH designation itself, compared with costs that are coextensive with listing. In two case studies of published economic analyses, we also specifically compare our treatment effects with the predicted costs of CH due to lost development opportunities or modifications to development projects.

[3] A natural extension to this paper is a test of whether land development rates in listed species' range space were lower from 1992 to 2011 than in similar areas completely outside of listed range space. We will look for evidence of this effect in a later paper.

2. Background

2.1. Regulatory Context for Critical Habitat Regulation under the Endangered Species Act

The ESA has the potential to create significant opportunity costs (Brown and Shogren 1998). Section 9 of the act prohibits any takings of listed species on private and public land. For example, the conversion of land from forest to residential use could be prevented by Section 9 if the forest contains a listed species or is considered listed species habitat. Section 7 of the act requires that federal actions do not jeopardize the continued existence of the species. Compliance with these sections could limit the development decisions that private landowners and public land managers are able to make, thereby generating opportunity costs.

The designation of CH for a listed species can create additional opportunity costs (Plantinga et al. 2014). Any proposed activity in CH areas that occur on federal lands, involve federal funding, or require a federal permit can be prevented or modified if the regulating agencies find that it would adversely modify the species' habitat. As Plantinga et al. note, "In order for the designation of critical habitat to have incremental economic effects, it must prevent otherwise economical activities, *excluding* those activities already prohibited by the jeopardy standard (section 7) or take restrictions (section 9)" (2014, 128). For example, Suckling and Taylor (2005) claim that a Hawaiian road was rerouted from a planned path through a CH to avoid costly consultation with FWS. They do not state, however, whether the rerouting was due to CH regulations, Section 7 or 9 of the act, or a combination of these regulations.

In addition, the mere presence of CH maps could modify land cover decisionmaking in other, more subtle ways. First, landowners in CH areas could be more hesitant to make land cover changes than landowners in non-CH listed species' ranges because of the preciseness of the CH maps versus the impreciseness of listed species' range space. Landowners in CH areas cannot claim that there is no official evidence to tie their land to ESA regulations. The landowner in a CH may suspect that his or her actions, especially any actions that result in a taking, will be scrutinized by federal authorities and conservation nonprofits, given that the land is officially in a regulatory zone.[4] Second, CH designation communicates the importance of the designated area for the recovery of the listed species and gives conservation-minded stakeholders incentive to

[4] On the other hand, a private landowner on land that was not deemed vital to a species' persistence and not officially linked to a species' range with a map published in the *Federal Register* might be more likely to avoid any scrutiny of his or her actions.

concentrate recovery activities in the area. Suckling and Taylor (2005) argue that in several cases, private CH landowners and government land managers have voluntarily cooperated on habitat management plans that otherwise would not have been created without the CH designation. Further, they say, CH could prompt conservation organizations to try to secure conservation easements or purchase lands within the CH area, which would block land development.

2.2. Previous Critical Habitat Cost Estimates

Several academic studies have measured the impact of CH designation on housing and land markets in a few areas of California (Zabel and Paterson 2006, 2011). Although these studies find some evidence of differences in economic activity inside CH boundaries versus outside, they are not able to attribute the differences to any specific provision of the ESA, nor are the cost lessons learned in these few case studies extrapolated to other CH areas. List et al. (2006) focus on the potential impact a CH designation had on the *timing* of development. They hypothesize that just prior to final designation but after announcement of the proposed CH, private interests in the soon-to-be CH would preemptively develop (or otherwise alter habitat) in order to avoid postdesignation regulatory restrictions on land use: the so-called "shoot, shovel, and shut up" (SSS) phenomenon. If this pace of development deviates from what would have occurred without CH designation, then, assuming rational land markets, the CH designation has generated a suboptimal land use trajectory and therefore an opportunity cost. List et al. find that parcels in proposed pygmy owl CH, which became part of the final CH a year later, were developed at a rate greater than nearby private parcels similar in every way except that they happened to lie immediately outside the proposed CH border. Likewise, Lueck and Michael (2000) find that landowners were more likely to harvest timber sooner when the forest plot was closer to red-cockaded woodpecker nests in North Carolina.

On the other hand, the regulating agencies themselves have estimated costs for almost all CH designations. However, this dataset of cost estimates is not as informative as it appears. First, the cost-calculating methodology and category of costs used in these studies have varied over time (Plantinga et al. 2014). Prior to 2001, only administrative and consulting costs were included in CH cost estimates Then, between 2001 and 2004, regulating agencies were mandated by a federal court ruling to assign *all* ESA-related costs expected to occur within a CH area to that CH. Therefore, Section 7 and 9–related costs that would have occurred in a CH area even if the CH was never designated were made part of the CH's cost estimate. Then, after another federal court decision in 2004, only the additional costs expected because of a CH were to be included in agency estimates of CH costs. Therefore, CH cost estimates are not necessarily comparable across time. Further, some cost estimates were prepared by consulting firms and others by the regulating agencies themselves. There is nothing to suggest that calculation methodologies are consistent across the various organizations.

In light of the continuing cost uncertainty and piecemeal nature of CH cost estimates, Plantinga et al. (2014) call for a comprehensive retrospective analysis to identify the actual scope and magnitude of economic costs engendered by CH, distinct from costs related to other portions of the ESA. While we agree with the need for such analysis, we do not believe it to be feasible given the data available at this time. We are not aware of a comprehensive dataset that would enable researchers to identify what decisions and choices have been made by regulators, landowners, land managers, and dam operators due to each separate part of the ESA. However, the data to identify land cover decisions caused or spurred by CH designation in certain time periods are now available. Whether the actions have been motivated by Section 7, Section 9, the CH rule itself, or the mere mapping of areas regulated by the ESA is unknown. Broadly speaking, we are not bothered by the lack of clear categorization. Our contribution is a consistent method for calculating a well-defined economic cost of regulation in specific areas of the landscape. Yes, we cannot apply our methods to all CH areas, given the limited years of conterminous US pixel-level land cover data, nor can we measure all economic opportunity costs created by CH designation, most importantly land management costs, because our data are limited to land cover. Yet this is the broadest *and* most consistent estimate of the economic impact of the ESA to date, despite its many flaws.

2.3. Critical Habitat Benefit Estimates

We do not estimate the benefits of CH designation in this study. The benefits of CH have gotten very little attention in the economics literature and only a small amount in the conservation biology literature (e.g., Suckling and Taylor 2005). Several researchers have noted that species with CH designation have better recovery scores (as assigned by the regulating agencies) than species without CH (Taylor et al. 2005; Suckling and Taylor 2005). However, how much of this increased recovery, if any, can be attributed to CH itself is unknown. One reason for the lack of researcher attention may be the odd mixed signals coming from the regulatory agencies regarding the benefits of CH. Despite their regulatory mandate to designate a species' CH immediately after its listing, the FWS and National Marine Fisheries Service (NMFS) have been loath to do so. As of early 2015, more than half of all listed species in the United States (873 of 1,577) still do not have a CH area. Both agencies argue that CH areas do not provide any additional protection to listed species above and beyond other ESA regulatory measures, and therefore the opportunity costs created by CH designation are not counterbalanced by *any* additional recovery or survival benefit (Corn et al. 2012).

3. Data

3.1. Critical Habitat Area Data

The US government has published digital maps for almost all final CH areas established between 1973 and 2013. With these maps, we have created a database of conterminous US CH areas for 310 species (Figure 1 and Tables 1–4).[5] We are particularly interested in the cohort of CH areas established between 1985 and 1994 (hereafter known as the Class of ’92) and between 1999 and 2003 (hereafter known as the Class of ’01) because their establishment matches the timing of US pixel-level land use data that drives our analyses (see Appendix A for lists of species in the two classes).

As Figure 1 demonstrates, CH areas, including the subsets that form the Classes of ’92 and ’01, are not randomly distributed in space. The Class of ’92 is concentrated the southwestern United States. The Class of ’01 is relatively more widespread, with CH areas in the Southeast, California, the Midwest, and the Northwest. The suggestion of selection bias in the Classes of ’92 and ’01 means that the conclusions we reach in this paper on the effect of CH regulations on land cover change may not necessarily be applicable to more recent and future CH designations. If the process of CH area selection has evolved since the early 2000s, or regulatory and landowner reactions to CH designation in parts of the country not represented by these two classes are different than what we find, then any extrapolations of our results beyond our studied set should be made with caution.

Spatial mismatch is not the only difference between the Classes of ’92 and ’01. Relative to the Class of ’01, the earlier class is composed of smaller CH areas that are distributed across poorer soils, more public lands, and colder temperatures (Table 2). In addition, the Class of ’92 covers, on average, landscapes with fewer people, lower incomes, and less valuable land as compared with the landscapes encompassed by the Class of ’01 CH areas (Table 3). Furthermore, the species mix protected by CH areas differs across the two classes. More than half of the CH areas in the earlier class protect the vital habitat of reptiles, amphibians, and fish,

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[5] We use the term *species* to refer separate listings under the ESA, whether they are for true species, subspecies, a distinct population segment (DPS), or evolutionarily significant unit (ESU).

whereas more than half of the CHs in the later class protect the vital habitat of plants and invertebrates (Table 1). Finally, at the time of designation, the Class of ’92 covered more seminatural and agricultural land than did the Class of ’01. The latter class contained more developed land and water in 2001 than the Class of ’92 did in 1992 (Table 4).

3.2. Breaking Up Critical Habitat Areas

Many CH areas are composed of multiple distinct polygons. Further, some CH areas are very large and spread out over multiple states. To reduce any bias that variation in CH extent could introduce into our analysis of the effect of CH designation on land cover change, we broke most CH areas into smaller spatial units to create a more reasonable size distribution of CH polygons for our matching analysis. We broke up CH areas in one of two ways. First, if a CH area is composed of multiple distinct polygons, we treated each distinct part of a CH as a separate geographic entity. Second, when whole CH areas or their distinct polygons encompass large areas, we split the areas or polygons by watershed, using the eight-digit hydrologic unit code (HUC8 watershed boundary) (USDA-NRCS 2014). Let i index CHs and i_k each distinct polygon of i. In the database used for the statistical analyses discussed below, 1992, 2001, and 2011 land cover (Jin et al. 2013) and 1992 and 2001 socioeconomic and biophysical data are described separately for each i_k. This treatment of the data results in 327 CH polygons that belong to the Class of ’92 and 743 CH polygons that belong to the Class of ‘01.

We also recorded the year in which each distinct CH polygon i_k first became subject to general ESA regulations. [6] For example, suppose species i was listed under the ESA in 1985, but its CH i was not established until 1992. Suppose one of CH i’s four distinct polygons, indexed by i_1, is in a watershed that has been in listed range space since 1975 (listed range space is defined at the level of HUC8 watershed boundary by NatureServe 2014). Suppose the other three distinct polygons of i—i_2, i_3, and i_4—are in HUC8 watersheds that have been in listed ranges since 1980. In this case, the area defined by the Class of ’92 CH polygon i_1 first became subject to general ESA regulations in 1975, and the areas defined by Class of ’92 CH polygons i_2, i_3, and i_4 first became subject to general ESA regulations in 1980.

[6] Despite the regulatory directive, CH is often not designated at the time of listing under the ESA. The majority of species (69%) had a gap between listing and CH establishment. It takes a median of 3.1 (mean = 5.1) years to designate a final CH for those species with CH areas, with a maximum delay of 30 years. In fact, in many cases a species’ CH area is found in the range of another species that was listed even earlier.

3.3. Control Polygons

We also created a set of 2,474 conterminous US control polygons. These control polygons are used to test the impact of CH designation on land cover change. Each control polygon is randomly located on a part of the US landscape that is subject to general ESA regulations but not CH regulations. In other words, all control polygons are in HUC8 watersheds that are classified as part of one or more listed species' range space (NatureServe 2014) but do not overlap CH areas.[7] Control polygons do not overlap each other and are located in just one HUC8 watershed (to mimic the CH areas being split by watershed boundary). The distribution of control polygon sizes matches the distribution of the sizes of CH polygons i_k. Of the 2,474 control polygons, 1,328 are roughly circular in shape, while 1,146 are buffers around streams. We created control polygons based on buffered streams to mimic some of the CH polygons, particularly for fishes, that are based on stream buffers. For each control polygon, we have described land cover as of 1992, 2001, and 2011 and the same biophysical and socioeconomic conditions in 1992 and 2001 used to describe the condition of CH polygons. The control polygon database also indicates when each control polygon was first subject to ESA regulations.

3.4. Covariate Data

We describe the land cover distribution within each CH and control polygon as of 1992, 2001, and 2011 using the National Land Cover Database (NLCD) datasets (Vogelmann et al. 2001; Homer et al. 2004; Jin et al. 2013). NLCD land cover categories include developed, agriculture (cropland plus pasture), barren, wetland, forest, grassland/shrub, and open water. We define the area of seminatural land cover in a polygon as the sum of its barren, wetland, forest, and grassland/shrub area. Polygon-level data on circa 1992 and 2001 biophysical, demographic, economic, and political conditions came from a variety of datasets. We describe these data in more detail in Section 4.

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[7] Because all CH areas are within one or more listed species' ranges, the counterfactual map can include only those areas that are also within one or more listed species' ranges. We are using the term "listed range space" to mean, for any given year, the space within the continental United States where at least one listed species "occurs." NatureServe (2014) identifies listed species' occurrence at the eight-digit hydrologic unit code (HUC8) watershed level. The data is a compilation of field study data and represents NatureServe's best estimate of listed species ranges across all taxa, but overestimates actual ranges. The data has no regulatory status.

3.5. Strengths and Weaknesses of the Data

All covariate data used to describe CH and control polygons are mapped at the spatial grain of a hectare. However, some of the covariate data have a native resolution at the county level (the land value, income, and presidential voting data, for example) or at 1 km^2 (the population data). Further, the NLCD datasets do not use the exact same land cover classifications across years, so only the published 1992–2001, 2001–06, and 2006–11 "change products" (Fry et al. 2009, 2011; Jin et al. 2013), which have a reduced number of land cover types, can be used for estimating land cover change. Specifically, we use the 1992–2001 change product for change between 1992 and 2001 and the 2001–06 and 2006–11 change products (which are harmonized) for change between 2001 and 2011 (Table 4). Further, the "developed" land category in the NLCD change products is quite broad and ranges from "areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses" where "impervious surfaces account for less than 20 percent of total cover" to "highly developed areas where people reside or work in high numbers" where "impervious surfaces account for 80 percent to 100 percent of the total cover."

Finally, the spatial grain of listed species ranges—that is, the HUC8 level watershed (NatureServe 2014)—varies in size and can be larger than counties. This means that listed range data consistently overestimate the actual range of the species: for example, the species may be known from only one location within the watershed. Occurrence in a watershed does not mean the species regularly occurs there, nor that the watershed has the resources to sustain the species for an indefinite time period. More specific species range maps exist for most vertebrates but not for most plants and invertebrates, so we decided to use a single dataset across all taxa.

4. Identification Strategy

To identify the effect that CH designation has on land cover change, we need to find a subset of control polygons that match the conditions found in the CH polygons at the time of CH designation. If the match is accurate, then differences in land cover outcomes in CH polygons versus the matched group can be interpreted as the effect of CH designation or treatment, separate from the effect of listing itself, since the control polygons are in listed range as well. In this section, we describe the process of finding the subset of control polygons that match CH polygons.

4.1. Matching Methods

Let y_{jn} indicate the percentage change in the area of j that is in land cover type n over time span T where $j = 1,\ldots J$ indexes all the possible areas on the landscape. In our case n is either developed (D), agriculture (A), or seminatural (SN). Let y_{1jn} indicate the outcome in polygon j when j is designated as CH at the beginning of period T. Let y_{0jn} indicate the outcome in polygon j when j is not designated as CH during time period T. Let $w_j = 1$ if polygon j was designated or treated and equal 0 otherwise. Therefore, the incremental impact of CH designation on change in n, or the average treatment effect (ATE) τ_n, is equal to

$$\tau_n = E[y_{1n} - y_{0n}|w = 1] \tag{1}$$

In other words, τ_n is expected change in land use n in CH polygons during T less what we could have expected to happen to land cover n during T if the CH polygons had not been designated (the counterfactual).

The outcomes y_{0n} and y_{1n} exist for all j during T, but we observe only one of them for each j: a polygon is either in CH or not during T. If y_n is the outcome, we observe then that

$$y_n = (1 - w)y_{0n} + wy_{1n} = y_{0n} + w(y_{1n} - y_{0n}) \tag{2}$$

If, at the beginning of time period T, we could have assigned CH to a random subset of polygons ($w_j = 1$) and assigned no CH treatment to another random subset of polygons ($w_j = 0$), then we could have claimed the sets of observed y_{1jn} and y_{0jn} were statistically independent from the choice of $w_j = 1$. From this we could have concluded the following (Glewwe 2014):

$$E[y_n|w = 1] = E[y_{1n}] \tag{3}$$

$$E[y_n|w = 0] = E[y_{0n}|w = 0] = E[y_{0n}|w = 1] = E[y_{0n}] \tag{4}$$

and

$$\tau_n = E[y_{1n}] - E[y_{0n}] = E[y_n|w = 1] - E[y_n|w = 0] \tag{5}$$

And to estimate τ_n we would use the following:

$$\hat{\tau}_n = \left(1/\textstyle\sum_{j=1}^{M} w_j\right) \sum_{j=1}^{M} w_j y_{1jn} - \left(1/\textstyle\sum_{j=1}^{M} 1 - w_j\right) \sum_{j=1}^{M} (1 - w_j) y_{0jn} \tag{6}$$

where M is the size of the set formed by the union of the treated and control area subsets, and $\hat{y}_{jn}$ is the observed land use change in polygon j.

Unfortunately, w_j is not randomly assigned but chosen according to ESA regulations, current scientific knowledge, and regulatory and political bias. Presumably, CH will be assigned to areas that are considered vital to imperiled species persistence. There is every reason to expect vitality to be determined by very specific biophysical and land cover features on the landscape that are not randomly distributed. In addition, regulators can consider economic costs, including the potential cost of prevented or delayed land development, when deciding on CH. In other words, it is very unlikely that w is statistically independent of y_0 and y_1.

However, we can still estimate τ_n if we make several assumptions. First, we assume the regulator's choice of w is strongly influenced by observable vector of variables $\mathbf{x}$. In other words, for all J areas on the US landscape, there exists some probability $0 < P[w = 1|\mathbf{x}] < 1$ that it will be designated CH. The expression $p(x) = P[w = 1|\mathbf{x}]$ is called the propensity score (Rosenbaum and Rubin 1983). Second, we assume that, conditional on the value of each area's $\mathbf{x}$, w is independent of y_0 and y_1. This means that expected land cover change in nontreated and treated areas is only conditional on $\mathbf{x}$, $E[y_0|\mathbf{x}]$ and $E[y_1|\mathbf{x}]$. This second assumption is known as ignorability of treatment (Rosenbaum and Rubin 1983). The two assumptions together are known as strong ignorability and allow us to claim that equation (5) holds in our problem.

Several statistical methods use strong ignorability to identify $\hat{\tau}_n$. We use matching methods. The basic idea behind matching is to compute counterfactual y_0s for each treated area. We can either find one unique match and its associated $\hat{y}_{0jn}$ for each observed $\hat{y}_{1jn}$ or find multiple matches and associated $\hat{y}_{0jn}$s for each observed $\hat{y}_{1jn}$. If we find multiple matches, we have to reduce the multiple values to a representative $\hat{y}_{0jn}$ value. In general,

$$\hat{\tau}_n = (1/K) \sum_{k=1}^{K} \left(\hat{y}_{1kn} - \sum_{q \in C(k)} \alpha_{kq} \hat{y}_{0qn} \right) \tag{7}$$

where $k = 1,\ldots,K$ indexes all the CH polygons on the landscape at the beginning of time period T, $q = 1,\ldots,Q$ indexes all the possible counterfactual areas on the landscape, $\hat{y}_{0qn}$ is a counterfactual outcome, $C(k)$ is the set of matched counterfactual outcomes assigned to k, and α_{kq} is the fractional weight of matched counterfactual outcome $\hat{y}_{0q}$. If we find one unique match for each observed $\hat{y}_{1kn}$, then the set $C(k)$ only has one member and $\alpha_{kq} = 1$. If we find multiple matches for each treated area on the landscape, then $C(k)$ has two or more members, $\alpha_{kq} < 1$ for all q, and $\sum_{q \in C(k)} \alpha_{kq} = 1$. See Appendix B for details on how $C(k)$ and α_{kq} can be estimated.

4.2. Relevant Covariates for Our Analysis

An accurate estimate of τ_n requires that the covariates in $\mathbf{x}$ are "balanced" across the treated and matched areas. In other words, the means of $\mathbf{x}$'s elements across the CH polygons need to be approximately equal to the means of $\mathbf{x}$'s elements across the matched control polygons. If balance is met, then the only difference between the two sets of polygons is treatment. Balance is more likely if **x** contains only variables that simultaneously influence treatment status and the outcome variable and variables that are unaffected by treatment (Sianesi 2004; Smith and Todd 2005). To meet this last criterion, variables in **x** should be either fixed over time or measured before or at the time of treatment.

Here we are considering only those polygons, both treated and untreated, that are in listed species' range space at the beginning of *T*. Therefore, **x** should include only variables that we believe simultaneously influence whether CH is applied to an area within listed range space and the subsequent land cover change observed within the CH polygons. First and foremost, the mix of land cover within listed range space areas at the beginning of *T* will affect treatment status and the outcome variable. Habitat vital to a listed species' persistence can be fulfilled only by certain land cover mixes in its range. Furthermore, land cover change rates in an area are a function of the mix of land cover present at the beginning of the period. For example, housing and cropland development will be more profitable in dry grasslands than in wet marshes. Biophysical conditions in an area are also important determinants in defining the most vital habitat areas (e.g., species prefer certain temperature and elevation niches) and development rates in an area (e.g., people prefer to live in temperate areas that are not too difficult to access).

Economic issues will also affect both treatment decisions and outcomes. Regulators may avoid establishing CH in areas with higher land values. Further, private land development is more likely in areas that have significant economic activity, are close to urban infrastructure, and are near private lots that have recently sold at high prices. At this same time, relatively high agricultural values in an area can reduce the rate of development. Finally, conservation organizations may be less active in CHs with higher land values because of limited budgets for land conservation.

Moreover, political preferences and regulatory biases across the landscape may affect both CH location and land cover change outcomes. For example, regulators may avoid placing CH in areas with voters who tend to find the land cover and use regulation most objectionable. Previous research has shown that regulatory agencies tend to allocate recovery funds to more charismatic species and are affected in general by various political variables when managing listed species (Easter-Pilcher 1996;, Doremus 1997; Waples et al. 2013). Such resource allocation and management bias could be in an issue in CH designation and management as well.

Finally, the year that an area was first included in *any* listed species' range, not just the species for which the CH was designated, is also part of **x**. We include this covariate for two reasons. First, typically there is a delay between listing and the establishment of CH. Therefore, this variable will affect the probability that an area will be placed in CH. In addition, by including this variable, we construct a control set of polygons that have been under ESA regulation, on average, as long as polygons that became CH at time *T*. This minimizes the portion of $\hat{\tau}_n$ that can be explained by the amount of time spent subject to ESA regulation before CH designation.

As we noted above, it is recommended that variables in $\mathbf{x}$ should either be fixed over time or measured at or near the beginning of *T*. Given that we evaluate two time frames in this analysis, CHs established circa 1992 (between 1985 and 1994) and CHs established circa 2001 (between 1995 and 2004), we have to create two covariate vectors, one centered on 1992 and the other centered on 2001. Let $\mathbf{x}_{92}$ indicate the vector of covariates used in the estimation of $\hat{\tau}_{92-01,n}$ and $\hat{\tau}_{01-11,92,n}$, the average treatment effect on the change in land cover *n* in Class of '92 CHs from 1992 to 2001 and 2001 to 2011, respectively. The vector $\mathbf{x}_{92}$ includes socioeconomic and biophysical data from circa 1992 and other fixed data. The exceptions to this timing are lot price per acre for recently developed parcels, cropland costs, and fraction of area in private land. These are 1990–97 average, 1997, and 2000 estimates, respectively.

Let $\mathbf{x}_{01}$ indicate the vector of covariates used in the estimation of $\hat{\tau}_{01-11,01,n}$, the average treatment effect on the change in land cover *n* in Class of '01 CHs from 2001 to 2011. The vector $\mathbf{x}_{01}$ includes socioeconomic and biophysical data from circa 2001 and other fixed data. The exceptions to this timing are lot price per acre for recently developed parcels and cropland costs. The vectors $\mathbf{x}_{92}$ and $\mathbf{x}_{01}$ include all socioeconomic and biophysical data we collected. We also construct alternative $\mathbf{x}_{92}$ and $\mathbf{x}_{01}$ that include only economic data and another set that includes only growth covariates. See Figure 2 and Appendix C for more details on $\mathbf{x}_{92}$ and $\mathbf{x}_{01}$.

4.3. Explaining Land Cover Change Rates across CHs and Their Matched Areas

Finally, after estimating a series of ATEs, we identify how economic and land availability characteristics affect land cover change rates in and out of CH polygons. We do this by regressing land cover change rates on economic and land availability characteristics in CH polygons and their matched polygons. Let the regression model be given by

$$q_j = (\boldsymbol{\beta} + C_j\boldsymbol{\gamma})\mathbf{S}_j + \boldsymbol{\theta}\mathbf{FWS}_j + \varepsilon_j \qquad (8)$$

where q_j is percentage change in polygon *j*'s area that is in developed, agricultural, or seminatural land cover from 1992 to 2001 or 2001 to 2011, $\mathbf{S}_j$ is a vector of economic and land availability characteristics in polygon *j*, C_j equals 1 if *j* is a CH polygon and equals 0 if it is a matched polygon, $\mathbf{FWS}_j$ is a set of dummy variables that indicates which USFWS region *j* is in, and $j = 1,\ldots,J$ indexes the set of CH and matched polygons. The vector $\mathbf{S}_j$ includes lot price per acre for recently developed parcels in *j* (measured in \$10,000/acre increments), cropland value per acre in *j* (measured in \$10,000/acre increments), percentage of *j* in developed land cover at the beginning of the relevant decade, percentage of *j* in agricultural land cover at the beginning of the relevant decade, percentage of *j* in public land as of 2000, and whether or not *j* is in a metropolitan county. The variables in $\mathbf{S}_j$ are also used in the matching analysis and are described in more detail in Appendix C.

By pooling our CH and matched control polygon observations, and interacting all independent variables with C_j, we estimate the average incremental impact of each independent variable on land cover change in CH polygons versus their matches over one or two decades. Specifically, $\hat{\beta}_p$ indicates the average impact of variable *p* on land cover change in matched control areas, $\hat{\gamma}_p$ indicates the average incremental impact of variable *p* on land cover change due to treatment, and $\hat{\beta}_p + \hat{\gamma}_p$ indicates the (total) average impact of variable *p* on land cover change in CH polygons. For example, $\hat{\beta}_0 + \hat{\gamma}_0$ indicates the impact that CH designation in and of itself has on the dependent variable, whereas $\hat{\beta}_0$ is the estimated intercept for the matched areas only. Or $\hat{\beta}_1 + \hat{\gamma}_1$ indicates the average percentage increase in the dependent variable in CH polygons for every \$10,000 increase in developed lot value, whereas $\hat{\beta}_1$ alone gives the average percentage increase in the dependent variable in matched polygons for every \$10,000 increase in recently developed lot value.

We estimate (8) for each unique class, land cover category, and decadal combination using the set of control areas selected by the most balanced nearest-neighbor match. We use two techniques to estimate (8): ordinary least squares (OLS) and a spatial error model (SEM). The SEM accounts for any unobserved spatial correlation in the polygon data. When interpreting regression results, we use SEM results in lieu of OLS results if the estimated spatial autocorrelation coefficient is statistically significant at a $p = 0.1$ level (see Elhorst 2014 for details on the SEM).

5. Results

As we have set up the analysis, a positive (negative) $\hat{\tau}$ value means that decadal change rates for the given land cover category were *greater* (*lower*) on average in CH polygons than in control polygons.[8] For example, suppose the area of developed land in Class of '92 CH polygons increased, on average, by 2.5 percent from 1992 to 2001. Further, suppose the area of developed land in the matched set of control polygons increased, on average, by 2.0 percent from 1992 to 2001. In this case, $\hat{\tau}_{92-01,D} = 0.5$ and would be reported in Tables 5 or 7 as 0.5 = 2.5 – 2.0. The results described below are based on matching analyses with vectors $\mathbf{x_{92}}$ and $\mathbf{x_{01}}$ that include all socioeconomic and biophysical data we collected. The ATEs with the alternative vectors $\mathbf{x_{92}}$ and $\mathbf{x_{01}}$ produce results very similar to those described below. Therefore, ATE results with these alternative covariate vectors are given in Appendix D.

5.1. Class of '92's ATEs

On average, using the two matching techniques that returned the most balanced set of control polygons, we find CH designation did not have a statistically significant effect on developed or agricultural land cover change in Class of '92 CH areas from 1992 to 2001 or 2001 to 2011 (Table 5). In other words, $\hat{\tau}_{92-01,n}$ and $\hat{\tau}_{01-11,92,n}$ are statistically no different than 0 for *n* = D (developed) and A (agricultural).

The Class of '92 results exemplify the importance of matching. When we compare the average developed and agricultural land cover change across *all* control polygons (see "no match" in Table 5) from 2001 to 2011 with these estimates for Class of '92 CH polygons, we *do* find statistically significant differences (though not for the 1992 to 2001 period). The rate of development was, on average, four times greater in control polygons from 2001 to 2011 than it was in Class of '92 polygons. Further, on average, Class of '92 polygons gained agricultural cover on average from 2001 to 2011, whereas, on average, control polygons lost agricultural lands. Yet once we restrict our comparison to matched control polygons for this scenario, the statistical significance disappears. In the developed land case, this is because the standard error of the ATE doubles once the control set is limited to the matched set. In the agricultural land cover case, this is because the loss in agricultural land is much smaller in the matched control set (Table 5).

While CH treatment did not have statistically significant impacts on developed or agricultural land cover change in Class of '92 areas when each land cover is considered

[8] The denominator in the percentage calculations is the area of the entire CH or control polygon. We use this denominator instead of area in the land cover type in the base year to avoid any infinite percentages (e.g., a CH polygon goes from 0 developed hectares in 1992 to 100 developed hectares by 2001).

separately, CH is associated with statistically significant net gains in seminatural land cover from 2001 to 2011 in these areas (Table 5). The change in seminatural cover is essentially the negative of the net change in developed *and* agricultural land. Class of ’92 CH polygons experienced, on average, a 1.29 percent increase in seminatural land cover compared with a 0.33 percent decline in matched control polygons (using the four neighbor matching technique).[9]

As we mentioned above, the “shoot, shovel, and shut up” (SSS) hypothesis states that some newly regulated landowners (or landowners newly aware of regulation, as the case may be) will quickly convert any habitat on their land to avoid eventual detection of the habitat by imperfectly informed regulatory bureaucrats. A larger-than-expected burst of developed and agricultural land cover change right after regulation would be consistent with this hypothesis.[10] A greater-than-expected loss in seminatural land cover immediately after regulation would also support the SSS hypothesis. In our case, the SSS hypothesis can be tested by the inequality comparisons $\hat{\tau}_{92-01,D} > \hat{\tau}_{01-11,92,D}$, $\hat{\tau}_{92-01,A} > \hat{\tau}_{01-11,92,A}$, and $\hat{\tau}_{92-01,SN} < \hat{\tau}_{01-11,92,SN}$. In other words, if the SSS phenomenon is real, CH polygons will experience greater habitat conversion than their untreated matches in the first decade of treatment, potentially to avoid detection by regulatory authorities. After this burst of land conversion in CH areas, the difference in conversion rates between treated and untreated areas would shrink and even possibly converge in the second decade of treatment as regulations become more enforced.

Paired *t*-tests of differences between $\hat{\tau}_{92-01,D}$ and $\hat{\tau}_{01-11,92,D}$, $\hat{\tau}_{92-01,A}$ and $\hat{\tau}_{01-11,92,A}$, and $\hat{\tau}_{92-01,SN}$ and $\hat{\tau}_{01-11,92,SN}$ provide some support for the existence of the SSS phenomenon (Table 6). Specifically, the average gain in developed land cover in Class of ’92 areas was significantly higher (in a statistical sense) from 1992 to 2001 than from 2001 to 2011, while gain or maintenance of seminatural land cover was statistically greater in the second decade of treatment than in the first (using the four neighbor match).

5.2. Class of ’01’s ATEs

As with the Class of ’92 CH polygons, when we restrict our comparison of Class of ’01 CH polygons to matched control polygons, the statistical significance of the ATE of CH

[9] We emphasize the nearest-neighbor matching results because the Mahalanobis matching method often results in up to 50% of CH polygons being dropped from the ATE calculation.

[10] Or if there is a CH proposal period, the burst might start right after proposal but before final approval of the CH area.

designation on developed and agricultural land change rates disappears (Table 7). We also find support for our matched methods just as with the Class of ’92 CH areas. When we compare the average agricultural land cover change statistics in Class of ’01 polygons with *all* Class of ’01 control polygons (not just the matched polygons), we do find a statistically significant difference (Table 7). This same comparison across *all* control polygons also reveals a statistically significant greater loss in seminatural land cover in Class of ‘01 CH polygons from 2001 to 2011. In other words, Class of ’01 CH areas retained more cropland and pasture on average than the entire set of control polygons. However, these effects of CH on land change rates disappear in the matched analysis.

5.3. Comparing the Class of ’92’s ATEs with the Class of ‘01’s ATEs

Finally, we can compare the ATEs between the two classes of CHs. First, if we compare the magnitude of ATEs for each set’s inaugural decade of treatment (1992 to 2001 for the Class of ’92 and 2001 to 2011 for the Class of ’01), we see that the Class of ’01 experienced greater rates of development vis-à-vis its matched set than the Class of ’92 did. Accordingly, the Class of ’01 also experienced a greater relative loss in seminatural land cover than the Class of ’92 in its first decades of treatment. This suggests a stronger SSS effect in the Class of ’01 than in the Class of ’92 (but we would need a second decade of treatment for the Class of ’01 to formally test this).

Second, when we compare ATEs across the two classes for the time period 2001 to 2011, we see that gains in developed land relative to matched controls are higher in Class of ’01 areas than in Class of ’92 areas. This difference is statistically significant regardless of the matching technique (Table 8). Again, this is suggestive of an SSS effect in CH treatment.

5.4. Explaining Land Cover Conversion Rates

Although we found few statistically significant differences in *average* land cover conversion rates between treated and matched polygons, this does not mean that CH treatment is immaterial to land cover change. Here we identify how economic and land availability variables differentially affect land cover change rates in CH polygons versus their matched control areas.

First, we summarize estimated equation (8) when q_j is percentage change in area j that is in developed land cover (Table 9). Both the lot price for developed land, and the percentage of area already in developed land cover as of 1992, had a statistically significant impact on the rate of change in developed land cover from 1992 to 2001 in CH and matched areas. During this decade, developers tended to add newly developed land to clusters of already developed land regardless of treatment status. Counter to expectations, lower lot prices attracted greater development rates in control polygons. However, more in line with expectations, higher lot prices incrementally attracted more 1992 to 2001 development in the CH polygons ($\hat{\gamma}_1 > 0$). Therefore, it appears that the financial returns to development had to be stronger in Class of ’92 CH polygons than in their matched areas to induce additional development. This suggests that CH designation, at least for the Class of ’92, did prevent some development on the margin.

From 2001 to 2011, the Class of ’92 experienced its second decade of treatment. Over this period, no independent variable explained (total) developed land cover change rates in Class of ’92 CH areas (as given by $\hat{\beta} + \hat{\gamma}$). Increases in developed land cover in matched control polygons during this time were explained by higher cropland values, more private land, and being close to a major metropolitan area. Cropland and developed land values are positively correlated (a correlation coefficient of 0.37 across our database of CH and control polygons), so the positive impact of increasing cropland prices on development rates is likely an indicator of greater development rates in non-CH areas with higher land values.

Changes in developed land cover from 2001 to 2011 in Class of ’01 areas and their matches were explained by a different pattern of covariates than for the Class of ’92 areas and their matches. Development rates in the Class of ’01 matched control polygons were not affected by land prices (see $\hat{\beta}_1$ and $\hat{\beta}_2$). The extent of developed area as of 2001 in a polygon had a positive effect on control polygon development in the subsequent decade but a negative effect on CH polygon development. Conversely, development in Class of ’01 CH polygons increased with both developed land and cropland prices.

The phenomenon of land prices having a statistically significant effect on land cover change rates only in CH areas versus their matched controls holds for agricultural land cover (Table 10). In the first decade of treatment for both the Class of ’92 (1992 to 2001) and the Class of ’01 (2001 to 2011), increases in cropland prices are associated with greater rates of agricultural development in CH polygons ($\hat{\beta}_2 + \hat{\gamma}_2 > 0$ for both) but not in their matched controls. A greater base of convertible seminatural land is also associated with greater rates of agricultural land development in CH polygons. In control areas, more private land and more potential agricultural land at the beginning of a decade (i.e., more seminatural cover at the beginning of the decade) are associated with gains in agricultural land cover. The differences in agricultural land cover change rates in and outside of CH areas could be explained by several phenomena. First, fears and uncertainties about CH-related regulations may mean that converting seminatural land to agriculture requires an above-average return. Second, it may also mean that agriculture is a more viable alternative in CH areas than in the areas selected for our matched controls. Outside of CH polygons, land cover change dynamics may be dominated by the developed land market, meaning agricultural land cover change in these areas is largely determined by factors other than cropland prices.

The change in seminatural cover is essentially the negative of the net change in developed and agricultural land. Further, gains in seminatural land mostly come from abandoned cropland (it is rare for physical structures and impervious surfaces to be converted to grassland or forest land cover). Therefore, given that land cover change in CH polygons is more responsive to cropland prices than in matched areas, it is not surprising to see similar results for seminatural cover in CH polygons (Table 11). For example, in CH areas, every additional \$10,000/acre increment in cropland value is associated with a 9.5 percent to 32.6 percent decline in seminatural cover in CHs ($\hat{\beta}_2 + \hat{\gamma}_2 < 0$ for all three class-decade combinations). In contrast, change in seminatural area in the matched control polygons is not affected by cropland prices except for the Class of ’92 in 2001–11. Further, gains in seminatural cover over a decade are more likely in CH polygons with a greater fraction of cropland in the first decade after CH designation ($\hat{\beta}_4 + \hat{\gamma}_4 > 0$ for the two relevant class-decade combinations). As mentioned above, to gain seminatural land cover, an area needs a base of land cover that can be converted to seminatural use.

Finally, for the Class of ’92, the extent of public land in its areas had a significant effect on seminatural land cover change in both decades of treatment, but in opposite directions. From 1992 to 2001, CHs with more public land *gained* seminatural land cover, while this variable did not influence changes in Class of ’92 matches. Conversely, from 2001 to 2011, CHs with more public land *lost* seminatural cover, while their matched areas with higher concentrations of public land gained seminatural cover.

5.5. Uncertainties

Although we have digital critical habitat maps for 310 species, we were limited to 87 species and their CHs: 43 species with CHs established circa 1992 and 44 with CHs established circa 2001 (Appendix A). We could not use CHs established in the 1970s and most of the 1980s to analyze the effect of regulatory treatment on land cover because continent-wide land cover maps at the appropriate scale do not exist for this period. Further, we cannot use CHs established after the early 2000s because of a lack of time necessary to establish a regulatory impact. Therefore, given that the subset of 90 CHs we use are not randomly distributed (Figure 1) and are not necessarily representative of all species with CHs or those species that may gain CHs soon, we are cautious in generalizing our results to all listed species with CHs.

6. Comparison with Agency Cost Projections

The cost of the CH rule has not been estimated in a regulatory impact analysis (RIA). In lieu of this missing cost estimate, we retrieve costs from economic impact analyses (EAs) summarized in the *Federal Register* (FR) notices that announced final CH designation for the 310 CH areas in our database. EAs have been conducted for 87 percent of these 310 CH areas and for 95 percent of the designations since 2001.[11] The EA methodologies vary widely: some consider only additional administrative costs and consultation expenses, whereas others include estimates of forgone development and other types of costs, which may or may not be specific to the CH designation. Variation in methods is partly the result of two conflicting court rulings. In 2001 the 10th Circuit Court of Appeals ruled in *NMCA v. US FWS* that the FWS should "conduct a full analysis of all of the economic impacts of a critical habitat designation, regardless of whether those impacts are attributable co-extensively to other causes" (the "co-extensive" approach).[12] However, subsequent rulings by the 9th Circuit Court of Appeals have allowed the FWS to use a "baseline" or "incremental" approach, where costs beyond just consultations may be considered, but not all costs co-extensive with the listing of a species, and in 2011 the US Supreme Court declined to take up appeals of the 9th Circuit rulings.[13]

We summarize Class of '92 and Class of '01 CH cost estimates from EAs in Figure 3. For consistency, we include only incremental approach cost estimates. We use this set because there are more incremental cost estimates than co-extensive estimates. Annualized cost estimates (2010$) vary from $0 (73 EAs) to over $100 million (the Atlantic salmon, *Salmo salar*).[14] The total annualized cost across all incremental EAs in our analysis, without double-counting multiple-species EAs, was $688.5 million (2010$).[15] The most common reasons provided for economic costs attributable to CH designation were administrative or consultation (67 species),

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[11] A revision to the ESA that requires an economic analysis to be published at the time of a *proposed* critical habitat designation went into effect on October 30, 2013.

[12] *New Mexico Cattlegrowers' Association v. US Fish and Wildlife Service*, 248 F.3d 1277 (10th Cir. 2001).

[13] *Gifford Pinchot Task Force v. US Fish & Wildlife Service*, 378 F.3d 1059 (9th Cir. 2004), amended, 387 F.3d 968 (9th Cir. 2004), and *Arizona Cattle Growers' Association v. Salazar*, 606 F.3d 1160, 1172 (9th Cir. 2010), cert. denied, 131 S. Ct. 1471 (2011).

[14] Of the 73 EAs with cost estimates of $0, 64 were included as an estimate of $0 "by inference"—that is, they were for species whose FR document included language such as "no significant economic impacts" or "few additional economic effects" of the CH designation.

[15] Most EAs present predicted CH costs not in annual terms but in 10- or 20-year terms. For example, a cost estimate could be $10 million over 20 years. We have annualized these numbers. Presumably, these costs are permanent.

development (53), and transportation (21). A single type of cost was provided for 56 species (typically administrative or consultation), while 39 species had EAs that cited more than one type of cost. In our two cohorts, EAs for Class of ’01 CH areas were more likely to provide some type of cost estimate (no NAs in the Class of ’01) and have a nonzero cost estimate.

We are interested in determining whether the EA cost predictions have proven to be accurate. However, we are limited in our ability to do that. First, we do not distinguish which part of the ESA caused land cover opportunity costs in CH areas; the costs in Figure 3 assume only causes from CH regulation. Second, the EAs often include costs beyond land cover opportunity costs. Clearly analysts have concluded that land management restrictions have created and will create nontrivial costs in certain CH areas. For example, nearly all of the costs attributed to the Atlantic salmon’s CH come from restrictions on dam use for hydropower. Despite these data mismatches, we believe we can use the estimated treatment effects to shed *some* light on the accuracy of the cost predictions in the FR notices. Namely, CHs that saw the greatest reductions in developed land area relative to their matches are most likely to have had the highest *land cover opportunity costs*, all else equal. And if these costs are a large part of the predicted CH costs, and if the cost predictions are largely accurate, then we should see a negative correlation between treatment effect and predicted cost. In Figure 4, we plot each Class of ’01’s developed land treatment effect, 2001 to 2011 change in developed land in the treated area less the same change in the CH area’s match, against its area-normalized EA cost prediction.[16] We also segregate plotted CH areas by their average lot value ($152,556 per acre is the median value across all CH polygons). All else equal, the *land cover opportunity costs* in areas with higher lot values should be greater.

According to Figure 4, predicted costs are much higher in CHs with higher lot values: the average per acre lot value is $311,799 in CH areas with a predicted cost above $0 and $132,168 in CH areas with a predicted cost equal to $0. Yet the correlation between predicted costs and developed land treatment effect is weak. The slope of the line fitted to the Figure 4 plot is negative, indicating that predicted costs increase as the ATE becomes more negative (less development occurs in a CH area relative to its match); however, this relationship is statistically insignificant. A finding of no relationship holds even if we limit the analyzed dataset just to those CHs with an average lot value of $152,556 per acre or higher. In Figure 5, we plot each

[16] We do not create a plot for Class of ’92 data because a large percentage of these CH designations do not have cost estimates in their FR notices.

Class of '01's agricultural treatment effect, 2001 to 2011 change in agricultural land in the treated area less the same change in the CH area's match, against its area normalized EA cost prediction. In this plot, CH areas are segregated by the median of cropland values across Class of '01 CH areas. Again in this plot, we find no systematic relationship between predicted CH costs and treatment effect.

We have found that predicted CH costs are not explained by land cover treatment effects. Of course, the predicted costs often include administrative and consultation costs and may include land or species management, energy, transportation, and utilities costs. There is no reason to believe that these types of costs would be explained by land cover treatment effects. This analysis makes clear that a final judgment on the accuracy of CH cost predictions requires measures of land management opportunity costs and other various opportunity costs caused by CH designation.

6.1. EA Case Studies

The analysis immediately above indicates that a more appropriate comparison of our results to EA cost predictions requires a decomposition of EA values into their component parts and then concentrating only on the predicted development costs. To demonstrate the possibility of such an analysis, we have closely read the EA cited in the FR CH designation of the Alameda whipsnake (*Masticophis lateralis euryxanthus*) and the EAs cited in several West Coast salmon and steelhead FR CH designations (specified below).[17] After isolating the development opportunity costs in these EAs, we compare them with the development opportunity cost we estimated for these CH areas.

The Alameda whipsnake's CH was first proposed in March 2000 and designated in October 2000.[18] In this FR notice, seven distinct CH areas (164,150 hectares [ha] total) in four California counties (Alameda, Contra Costa, San Joaquin, and Santa Clara) in the Bay Area were designated. In the economic analysis section of this FR notice, the FWS stated that "no economic impacts are expected from critical habitat designation above and beyond that already imposed by listing the Alameda whipsnake." The FWS acknowledged that a number of economic activities could be affected by the species listing itself but contended that these restrictions would occur

[17] 62 FR 64306 (December 5, 1997), 63 FR 32996 (June 17, 1998), 64 FR 14528 (March 25, 1999), and 64 FR 41835 (August 2, 1999).

[18] 65 FR 58933 (October 3, 2000).

regardless of CH designation—in part because all of the proposed CH areas were considered to be occupied by whipsnakes. In the FR, the FWS also acknowledged that CH designation could affect real estate values, but only temporarily, the agency contended.

Less than a year after CH designation, the Home Builders Association of Northern California filed a lawsuit against the FWS to challenge the rule.[19] As a result of the lawsuit, the FWS was ordered to complete a new final rule, which was subsequently proposed in 2005 and made final (along with a new economic analysis prepared by CRA International) in 2006.[20] The new EA considered 82,290 ha as proposed CH, while in the final 2000 rule, 62,659 ha in seven distinct areas were designated as CH (38 percent of the CH area from 2000). The total real estate development impact of CH designation was predicted to be $531,775,546 in lost real estate value over 20 years, or approximately $54.3 million per year (2010$; see Table 12) (CRA International 2006).

The newer EA was conducted after *NMCA v. US Fish & Wildlife*.[21] As a result, CRA International did not distinguish what impacts would have occurred with listing but in the absence of CH; in other words, the $532 million in predicted cost was a co-extensive prediction. In CRA's estimate, the company considered regional growth projections, effects of prior regulation on land development, development probabilities within CH units, indirect effects of CH on development projects (avoidance, mitigation, and compensation), and the effect of time delays due to the Section 7 consultation process or other compliance requirements. The EA also estimated regional economic effects (i.e., secondary effects due to reduced development) as $14.3 million in the two counties, with the largest effects on residential home construction (Contra Costa and Alameda), but this was considered a very small effect (<0.02 percent of regional output) and not included in the total cost estimate. Because the $532 million cost estimate was based on a scenario where avoidance requirements make some land off-limits to development, we conclude that it is comparable to our land cover opportunity cost for this species, which is based on actual development rates from 2001 to 2011 (conversion of seminatural land to developed land).

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[19] *Home Builders Association of Northern California et al. v. US Fish and Wildlife Service et al.* (268 F. Supp. 2d 1197).

[20] 71 FR 58176 (October 2, 2006).

[21] *New Mexico Cattlegrowers' Association v. US Fish and Wildlife Service*, 248 F.3d 1277 (10th Cir. 2001).

The 12 salmon and steelhead ESUs included in our second EA case study are from four species: chinook salmon (*Oncorhynchus tshawytscha*), chum salmon (*Oncorhynchus keta*), sockeye salmon (*Oncorhynchus nerka*), and steelhead (*Oncorhynchus mykiss*) from Washington, Oregon, and Idaho. CH was originally proposed for many of these ESUs at listing, but all 12 were part of a final rule designating CH in 2000. In the economic analysis section of this FR, NMFS stated that it was considering only the incremental effects "above the economic impacts attributable to listing or attributable to authorizes other than the ESA," and since the ESUs occupied all of the range considered for CH, "the designation will result in few, if any, additional economic effects beyond those that may have been caused by listing and by other statutes."

These fish stocks, like the Alameda whipsnake, were also the focus of lawsuits challenging the adequacy of economic impact predictions and timeliness of CH designation.[22] A timeline was agreed on and approved by the DC District Court, with a revised CH designation published as a final rule in 2005 along with a final economic analysis produced by NMFS (NFSC 2005).[23] The revised CH included 33,201 kilometers (km) of lake, riverine, and estuarine habitat and 3,721 km of marine nearshore habitat, with over 28 million ha in the three states (Washington, Oregon, and Idaho). In the EA, NMFS referred to the court's decision in *NMCA v. US Fish & Wildlife* and stated that its estimate of impacts included both co-extensive impacts (i.e., those associated with habitat-modifying actions covered by listing) and incremental impacts (i.e., those solely attributable to CH designation).[24] The annual economic impact of CH designation, co-extensive with listing, for all 12 ESUs was published as $243,709,179 (NFSC 2005), but with the exclusions identified in the FR, this was reduced to an annual cost of $201.2 million from all cost categories.[25]

The ESUs' EA examined the 13 types of activities that could potentially affect habitat: dams (hydropower and nonhydropower), federal lands management (wilderness and nonwilderness), grazing, transportation projects, utility line projects, sand and gravel mining, instream activities (dredging and nondredging), EPA National Pollutant Discharge Elimination

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[22] *Pacific Coast Federation of Fishermen's Associations et al. v. NMFS* (Civ.No. 03-1883).

[23] 70 FR 52630 (September 2, 2005).

[24] *New Mexico Cattlegrowers' Association v. US Fish and Wildlife Service*, 248 F.3d 1277 (10th Cir. 2001).

[25] The annual costs represent a midpoint between low and high estimates from the EA, using a discount rate of 7%. The total cost for the 12 ESUs is not the sum of costs for an individual ESU, since ESUs co-occur in some individual watersheds. In those cases, the maximum cost per watershed for any of the 12 ESUs was used a single time to count toward the total (NFSC 2005).

System (NPDES) permitted activities, agricultural pesticide applications, and residential and commercial development. Since our treatment effect is comparable only to estimated costs to development, we pulled out those specific estimates for each ESU, which varied from 0 percent to 11.4 percent of the total annual cost. Since the primary elements of salmon and steelhead habitat are aquatic, NMFS made the assumption that CH designation would not affect the supply of developable land itself. Rather, they reasoned that required modifications to development projects typically occur through stormwater permits and used an estimate for the cost of a stormwater management plan that would satisfy requirements relevant for salmon habitat. NMFS acknowledged the concern of commenters on proposed CHs that this designation could increase the price of developed land and housing, thereby leading to less development than would otherwise occur, but stated that consultations are relatively rare for development projects (NMFS used a probability of 6 percent in the EA) and average project modification costs are modest (it used a midpoint estimate of $235,000/project).

Similarly to our overall analysis of EA cost estimates from the FR (Figures 4 and 5), EA development opportunity cost estimates for the Alameda whipsnake and the 12 fish stocks were not correlated with the developed land cost we calculated from our average treatment effects (see Appendix E for cost calculations; Pearson's r = 0.12, P = 0.685 for our land cost estimate with EA development cost). In the EAs, annual development costs ranged from $0 to $54.2 million, while our calculated annual land cover opportunity costs ranged from –$1.0 million to +$7.3 million (all 2010$; Table 12). As noted above, only the Alameda whipsnake estimate of development cost should be considered directly comparable to our estimates, since that EA explicitly considered the cost of habitat protection (albeit co-extensively with listing) on development within critical habitat units. And in fact, our results show a negative influence of CH on development rates there, compared with matching polygons (a negative average treatment effect), and the second-highest estimate of land cover opportunity costs ($7.258 million annually). For the 12 fishes, there were both positive and negative treatment effects, and the three highest estimates of development costs from the EA (Lower Columbia and Upper Willamette River chinook salmon ESUs and Upper Willamette steelhead ESUs) had positive treatment effects and therefore "negative" costs (Table 12). And although high costs for the Alameda whipsnake (both our estimate and in the EA) can be explained in part by high land values there, there was no correlation of the average urban returns value we used with our developed land cost estimate (Pearson's r = 0.33, P = 0.27).

A next stage for our research is, to the extent possible, to separate CH costs listed in FR notices into the three major cost categories: land cover costs, land management costs, and administrative/consulting. Such a separation would allow us to directly compare the land cover costs we calculate in this project and to complete a critique of CH-created land management opportunity cost estimates as well. We recommend that EAs created as part of proposed CHs, which are now required, continue to break up cost estimates into logical categories and to clearly distinguish between incremental costs of CH and (if included) costs that are co-extensive with listing.

7. Conclusions

Our analysis indicates that CH designation, or more precisely, designation for the fraction of CH designations that we were able to analyze, did not, on average, significantly affect land cover change in impacted areas on the US landscape. Average rates of land conversion to developed and agricultural cover were statistically equal to 0 for both groups of CH designates we analyzed. A higher-than-expected average gain in seminatural land cover in Class of ’92 CH areas from 2001 to 2011 is the one statistically significant treatment effect we found. Whether this “time lag” is replicated in the Class of ’01 CH areas from 2011 to 2021 or continues in the third decade of treatment for Class of ’92 CH areas remains to be seen. However, this effect should also be seen in the context of existing land cover: CH areas on average start out with approximately 75 percent seminatural land cover (Table 4).

Our results provide some support for the existence of a “shoot, shovel, and shut up” (SSS) or preemptive development dynamic. We find that landowners in newly established CH areas may have developed more quickly than they would have otherwise, possibly to avoid any potential conflicts with the CH regulations in particular or ESA regulations in general (Table 6). Although most of these areas would have been subject to ESA regulations for some time (because of typical delays of about three years between listing and CH designation), recall that CH maps are one of the few ways that a landowner can know for sure that his or her land is in a listed species’ range. However, we are hesitant to give full support to any evidentiary finding of the SSS for several reasons. First, a full decade is not the ideal time period to look for an SSS effect; shorter time periods would be more appropriate. Second, SSS behavior may be more often expressed by land cover changes too small to be registered by the land cover maps we used in this analysis or by land management changes that the land cover maps are not designed to register. Finally, we wonder if SSS is an issue we should even worry about. The average treatment effect magnitudes that we used to find evidence of the SSS effect are very small. So even if statistical evidence for the SSS effect is significant, its actual impact on species persistence may be minimal.

While CH designation on average does not affect the overall rates of land cover change, CH designation *does* appear to modify the impact of land cover change drivers. Generally, land prices have had more impact (statistically) on decisions within CH polygons than those made on landscape areas subject to ESA regulations but not designated as CH areas. Land cover change decisions in the untreated polygons tend to have been driven more by clustering and land availability concerns. All of this suggests that CH treatment has increased landowner uncertainty and that conversion to developed and agricultural use in CH polygons has, on average, required a return premium.

All of this evidence leads us to conclude that the establishment of CH areas has only little or marginal impact on land cover decisions in impacted areas. Why? First and foremost, it simply may be that CH regulations and the additional attention that CH maps can bring to areas subject to all of the various ESA regulations have little bite. In other words, it may be that very few people and institutions pay attention to CH designations. Further, it is possible that the impact of CH designation on overall land cover change rates is insignificant because CH areas are established where economic activity is minimal and is expected to remain minimal. As stated in the statute, “The Secretary may exclude any area from critical habitat if he determines that the [economic] benefits of such exclusion outweigh the benefits of specifying such area as part of the critical habitat, unless he determines, based on the best scientific and commercial data available, that the failure to designate such area as critical habitat will result in the extinction of the species concerned.” In other words, the CH area designation process likely incorporates cost minimization as one of its objectives. Therefore, maybe it is not surprising to find CH designation having little impact on land cover choices.

Although we argue that CH designation constrains land cover choice minimally, a thorough opportunity cost assessment of CH designation would need to also take into account any land management impacts of designation (e.g., changes to forestry or grazing practices). Therefore, we cannot conclude that *all* opportunity costs of CH designation above and beyond the opportunity costs of ESA listing are minimal. However, our results indicate that it is very unlikely that such costs will typically be high. Ultimately, this also makes us question the very rationale for the CH regulation in the first place. If it is not affecting land cover choice, is it actually helping the biodiversity it was designed to protect?

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Tables and Figures

Table 1. Conterminous US CHs by Establishment Cohort and Species Type

		Species type					
Cohort	Total CHs	Plants	Inverts	Fish	Herps	Birds	Mammals
1985–94 (Class of ’92)	43	11	1	24	1	2	4
1999–2003 (Class of ’01)	44	21	5	16	1	1	0
All CHs	310	89	82	83	19	17	20

Notes: *Inverts* includes all invertebrates; *Herps* includes reptiles and amphibians.

Table 2. Means and Standard Deviations of Biophysical Conditions by Conterminous US CH Cohort

Cohort	Total area (km^2)	Avg. % of area in good soils[a]	Avg. % of area in private land[b]	Monthly avg. temp. (C) in area over winter months[c]	
				1961–90	1990–2009
1985–94 (Class of ’92)	31,551	14.2 (29.5)	46.6 (38.3)	0.77 (4.3)	1.42 (4.4)
1999–2003 (Class of ’01)	51,500	30.3 (28.7)	62.8 (33.1)	5.14 (5.5)	5.63 (5.6)
All CHs	449,486	28.2 (30.2)	59.9 (36.4)	5.04 (5.5)	5.68 (5.5)
Contiguous US	7,824,147	45.3	73.3	–0.90 (6.81)	–0.13 (6.82)

[a] Good soils are those in land capability classes (LCCs) I–IV versus V–VIII (USDA-NRCS definitions; see http://www.nrcs.usda.gov/).
[b] As of 2000.
[c] Winter months are December, January, and February.

Table 3. Means and Standard Deviations of Socioeconomic Conditions by Conterminous US CH cohort

Cohort	Per acre lot price for recently developed parcels (1997$)[a]	Per acre cropland price (1997$)[b]	Pop. density (people/ha)[c]	Per capita income (2000$)[c]
1985–94 (Class of ’92)	99,269 (76,009)	851 (548)	0.29 (1.29)	22,535 (4,173)
1999–2003 (Class of ’01)	242,213 (189,035)	1,514 (1,080)	0.73 (1.58)	27,226 (8,422)
All CHs	156,583 (153,526)	1,343 (927)	0.78 (2.38)	24,282 (6,236)
Contiguous US	62,296	931	0.27	22,506

[a] 1990–97 average.
[b] 1997 value.
[c] Population density and per capita income are from 2000.

Table 4. Means and Standard Deviations of Land Cover by Conterminous US CH Cohort Using 1992–2001 and 2001–11 Change Products

	Avg. % of area in developed		Avg. % of area in agriculture		Avg. % of area in seminatural	
1992–2001 change product	1992	2001	1992	2001	1992	2001
1985–94 (Class of ’92)	5.9 (14.2)	6.2 (14.7)	8.7 (15.9)	9.0 (16.3)	75.5 (31.0)	74.7 (31.7)
1999–2003 (Class of ’01)	8.1 (8.2)	8.4 (8.6)	5.1 (7.3)	4.4 (6.7)	73.2 (25.4)	75.4 (23.2)
All CHs	7.9 (13.6)	8.2 (13.8)	8.6 (16.2)	7.9 (14.6)	75.7 (26.3)	76.3 (25.6)
2001–2011 change product	2001	2011	2001	2011	2001	2011
1985–94 (Class of ’92)	5.0 (11.8)	5.0 (12.0)	8.5 (18.4)	8.5 (18.2)	75.8 (32.3)	76.3 (31.4)
1999–2003 (Class of ’01)	10.4 (15.8)	9.2 (9.3)	4.0 (6.3)	4.0 (6.3)	73.6 (25.7)	75.0 (23.2)
All CHs	9.3 (16.7)	8.8 (14.6)	7.5 (14.8)	7.8 (14.8)	75.8 (26.9)	76.2 (25.9)

Notes: Open water is the major category not included in this table. The 1992–2001 change product was used for land cover change rates from 1992 to 2001. The 2001–11 change product was used for land cover change rates from 2001 to 2011.

Table 5. The Difference in Percentage Change in Land Covers in Class of ’92 CH Areas vs. Matched Areas, 1992–2001 and 2001–11

LU	Decade	Matching technique	Avg. treat. effect = treated – controls	Std. error	*t*-stat	Mean bias	CHs on support
D	92–01	No match	–0.04 = 0.21 – 0.24	0.09	–0.43	NA	NA
		No match	–0.03 = 0.21 – 0.23	0.09	–0.33	NA	NA
		4 N, cal. (0.02) (pars.)	0.05 = 0.21 – 0.17	0.14	0.32	2.85	305
		Mahal., cal. (1.5) (pars.)	0.02 = 0.13 – 0.12	0.19	0.10	1.40	222
	01–11	No match	–0.31 = 0.09 – 0.40	0.15	–2.07**	NA	NA
		No match	–0.25 = 0.09 – 0.35	0.13	–1.99**	NA	NA
		4 N, cal. (0.02) (pars.)	–0.30 = 0.09 – 0.39	0.29	–1.06	2.85	305
		Mahal., cal. (1.5) (pars.)	–0.12 = 0.02 – 0.14	0.27	–0.45	1.40	222
A	92–01	No match	0.23 = 0.04 + 0.19	0.22	1.07	NA	NA
		No match	0.28 = 0.04 + 0.24	0.22	1.28	NA	NA
		4 N, cal. (0.02) (pars.)	0.16 = 0.05 + 0.10	0.33	0.48	2.85	305
		Mahal., cal. (1.5) (pars.)	–0.23 = 0.04 – 0.27	0.45	–0.51	1.40	222
	01–11	No match	0.40 = 0.14 + 0.26	0.16	2.51**	NA	NA
		No match	0.38 = 0.14 + 0.23	0.16	2.34**	NA	NA
		4 N, cal. (0.02) (pars.)	0.24 = 0.16 + 0.08	0.17	1.38	2.85	305
		Mahal., cal. (1.5) (pars.)	0.12 = 0.23 – 0.11	0.46	0.26	1.40	222
SN	92–01	No match	0.45 = 0.20 + 0.24	0.24	1.87*	NA	NA
		No match	0.38 = 0.20 + 0.17	0.24	1.56	NA	NA
		4 N, cal. (0.02) (pars.)	0.46 = 0.23 + 0.23	0.45	1.03	2.85	305
		Mahal., cal. (1.5) (pars.)	0.92 = 0.53 + 0.39	0.65	1.42	1.40	222
	01–11	No match	1.54 = 1.29 + 0.24	0.28	5.52***	NA	NA
		No match	1.52 = 1.29 + 0.22	0.28	5.50***	NA	NA
		4 N, cal. (0.02) (pars.)	1.63 = 1.29 + 0.33	0.65	2.49**	2.85	305
		Mahal., cal. (1.5) (pars.)	0.48 = 0.23 + 0.24	0.57	0.84	1.40	222

Notes: D = developed, A = agricultural, SN = seminatural. The standardized bias should be less than 5% after matching (Rosenbaum and Rubin 1983). At 5% or less, the covariates are well balanced and a good control group has been built. A CH observation is on support if its propensity score is in the treatment and comparison group propensity score overlap. All ATEs are derived using the “parsimonious” versions of $\mathbf{x}_{92}$ and $\mathbf{x}_{01}$ (see Appendix C). All matching is done with the STATA ADO file psmatch2. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

Table 6. Paired *t*-test of the Hypotheses $\hat{\tau}_{92-01,D} - \hat{\tau}_{01-11,92,D} > 0$, $\hat{\tau}_{92-01,A} - \hat{\tau}_{01-11,92,A} > 0$ and $\hat{\tau}_{92-01,SN} - \hat{\tau}_{01-11,92,SN} < 0$

Matching technique	H_A: $\hat{\tau}_{92-01,D} > \hat{\tau}_{01-11,92,D}$		H_A: $\hat{\tau}_{92-01,A} > \hat{\tau}_{01-11,92,A}$		H_A: $\hat{\tau}_{92-01,SN} < \hat{\tau}_{01-11,92,SN}$	
4 N, cal. (0.02) (pars.)	0.05 (0.14) > –0.30 (0.29)		0.16 (0.33) > 0.24 (0.17)		0.46 (0.45) < 1.63 (0.65)	
Mahal., cal. (1.5) (pars.)	0.02 (0.21) > –0.12 (0.27)		–0.23 (0.45) > 0.12 (0.46)		0.92 (0.65) < 0.48 (0.57)	
	t-stat	Pr(*T* > *t*)	*t*-stat	Pr(*T* > *t*)	*t*-stat	Pr(*T* < *t*)
4 N, cal. (0.02) (pars.)	2.26**	0.012	–0.28	0.61	–1.62*	0.053
Mahal., cal. (1.5) (pars.)	0.78	0.22	–0.97	0.83	0.62	0.733

Notes: The null hypotheses are that the average treatment effects on developed, agriculture, and seminatural land use change are equal across the two decades.

Table 7. The Difference in Percentage Change in Land Covers of ’01 CH Areas vs. Matched Areas, 2001–11

LU	Matching technique	Avg. treat. effect = treated – controls	Std. error	*t*-stat	Mean bias	CHs on support
D	No match	0.14 = 0.48 – 0.35	0.11	1.27	NA	NA
	No match	0.09 = 0.48 – 0.40	0.12	0.74	NA	NA
	3 N (quad.)	0.19 = 0.47 – 0.28	0.16	1.18	6.33	654
	Mahal., cal. (1.5) (pars.)	0.22 = 0.27 – 0.05	0.14	1.52	1.11	386
A	No match	0.24 = 0.01 + 0.23	0.11	2.14**	NA	NA
	No match	0.26 = 0.00 + 0.26	0.11	2.38**	NA	NA
	3 N (quad.)	–0.09 = –0.01 – 0.08	0.14	–0.62	6.33	654
	Mahal., cal. (1.5) (pars.)	0.09 = 0.12 – 0.04	0.37	0.23	1.11	386
SN	No match	–0.66 = –0.88 + 0.22	0.19	–3.50***	NA	NA
	No match	–0.64 = –0.88 + 0.24	0.19	–3.38***	NA	NA
	3 N (quad.)	–0.34 = –0.77 + 0.42	0.33	–1.05	6.26	654
	Mahal., cal. (1.5) (pars.)	–0.18 = –0.42 + 0.24	0.55	–0.32	1.11	386

Notes: D = developed, A = agricultural, SN = seminatural. The 3 N results are based on the propensity score estimated with the “quadratic” model, and the Mahal., cal. (1.5) results are based on the propensity score estimated with the “parsimonious” model (see Appendix C). All matching is done with the STATA ADO file psmatch2. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

Table 8. *t*-test of the Hypotheses $\hat{\tau}_{01-11,92,D} - \hat{\tau}_{01-11,01,D} \neq 0$, $\hat{\tau}_{01-11,92,A} - \hat{\tau}_{01-11,01,A} \neq 0$ and $\hat{\tau}_{01-11,92,SN} - \hat{\tau}_{01-11,01,SN} \neq 0$

Matching technique	H_A: $\hat{\tau}_{01-11,92,D} \neq \hat{\tau}_{01-11,01,D}$		H_A: $\hat{\tau}_{01-11,92,A} \neq \hat{\tau}_{01-11,01,A}$		H_A: $\hat{\tau}_{01-11,92,SN} \neq \hat{\tau}_{01-11,01,SN}$	
Nearest N	–0.30 (0.29) ≠ 0.19 (0.16)		0.24 (0.17) ≠ –0.09 (0.14)		1.63 (0.65) ≠ –0.34 (0.33)	
Mahal., cal. (1.5)	–0.12 (0.27) ≠ 0.22 (0.14)		0.12 (0.46) ≠ 0.09 (0.37)		0.48 (0.57) ≠ –0.18 (0.55)	
	t-stat	Pr(|*T*| > |*t*|)	*t*-stat	Pr(|*T*| > |*t*|)	*t*-stat	Pr(|*T*| > |*t*|)
Nearest N	–2.92***	0.004	2.14**	0.61	3.08***	0.002
Mahal., cal. (1.5)	–1.97**	0.049	0.17	0.87	1.24	0.22

Notes: The null hypotheses are that the average treatment effects on developed, agriculture, and seminatural land use change are equal across the two classes from 2001 to 2011. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

Table 9. The Effects of Economic and Land Availability Characteristics on Percentage Change in Developed (D) Land Use Area

Class	'92						'01		
Decade	92–01			01–11			01–11		
Variable (p)	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}+\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}+\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}+\hat{\gamma}$
Constant (0)	0.332 (0.199)*	–0.14 (0.25)	0.19 (0.24)	–0.26 (0.36)	0.34 (0.45)	0.08 (0.43)	0.15 (0.47)	–0.43 (0.36)	–0.27 (0.45)
Developed lot price (1)	–0.03 (0.01)***	0.03 (0.01)**	0.007 (0.011)	–0.027 (0.016)*	0.03 (0.03)	$-4.4\text{x}10^{-4}$ (0.02)	–0.01 (0.02)	0.06 (0.02)***	0.05 (0.01)***
Cropland cost (2)	0.66 (0.89)	1.25 (1.98)	1.91 (1.80)	8.97 (1.69)***	–7.33 (3.55)**	1.64 (3.20)	1.01 (1.52)	2.468 (1.922)	4.17 (1.32)***
% of area in dev. at beginning of decade (3)	0.035 (0.01)***	–0.003 (0.008)	0.03 (0.01)***	0.01 (0.01)	–0.005 (0.02)	0.01 (0.01)	0.024 (0.01)***	–0.04 (0.01)***	–0.013 (0.008)*
% of area in ag. at beginning of decade (4)	0.001 (0.003)	0.007 (0.007)	0.008 (0.006)	–0.004 (0.006)	0.004 (0.013)	$-5.8\text{x}10^{-4}$ (0.01)	–0.003 (0.005)	0.001 (0.012)	–0.002 (0.011)
% of area in public land (5)	0.03 (0.17)	–0.41 (0.29)	–0.37 (0.24)	–0.52 (0.31)*	0.115 (0.518)	–0.40 (0.43)	–0.28 (0.33)	–0.21 (0.43)	–0.49 (0.30)*
In metro county (6)	0.27 (0.17)	–0.37 (0.24)	–0.10 (0.18)	0.64** (0.31)	–0.58 (0.42)	0.06 (0.30)	0.22 (0.31)	–0.59 (0.43)	–0.38 (0.33)
N	799			799			1,202		
R^2 (OLS) / $\hat{\lambda}$ (SEM)	0.14			–0.23 (0.13)*			0.35 (0.06)***		
Model	OLS			SEM			SEM		

Notes: For a given class and decade, $\hat{\beta}_p$ indicates the average impact of variable p on developed cover change in matched control areas, $\hat{\gamma}_p$ indicates the average incremental impact of variable p on developed cover change due to treatment, and $\hat{\beta}_p + \hat{\gamma}_p$ indicates the (total) average impact of variable p on developed cover change in CH polygons; equation (8). Developed lot price and cropland cost are in \$10,000/acre units. All regression models include dummy variables for each FWS region. In the spatial error model (SEM), the weight matrix is given by the normalized inverse matrix of Euclidean distances between observations. Distances are measured from the centroids of polygons. $\hat{\lambda}$ is the estimated SEM coefficient associated with the spatially correlated errors. The spatial regressions were done with the STATA ADO files spatwmat, spatdiag, and spatreg. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

Table 10. The Effects of Economic and Land Availability Characteristics on Percentage Change in Agricultural (A) Land Use Area

Class	'92						'01		
Decade	92–01			01–11			01–11		
Variable (p)	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}+\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}+\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}+\hat{\gamma}$
Constant(0)	–0.20 (0.52)	0.74 (0.64)	0.54 (0.64)	0.84 (0.26)***	–0.54 (0.33)	0.30 (0.33)	0.70 (0.33)**	–0.52 (0.25)**	0.19 (0.31)
Developed lot price (1)	0.029 (0.023)	–0.03 (0.04)	4.68×10^{-4} (0.03)	–0.001 (0.012)	–0.01 (0.02)	–0.01 (0.02)	–0.02 (0.01)	0.01 (0.01)	–0.01 (0.01)
Cropland cost (2)	–0.56 (2.20)	10.00 (4.96)**	9.44 (4.51)**	–1.27 (1.13)	0.81 (2.52)	–0.46 (2.30)	0.18 (1.09)	2.13 (1.36)	2.32 (0.91)**
% of area in dev. at beginning of decade (3)	–0.02 (0.01)*	-2.2×10^{-4} (0.02)	–0.02 (0.015)	–0.005 (0.006)	–0.007 (0.011)	–0.01 (0.01)	–0.02 (0.01)***	0.02 (0.01)**	0.001 (0.006)
% of area in ag. at beginning of decade (4)	0.001 (0.007)	–0.06 (0.02)***	–0.05 (0.02)***	–0.01 (0.004)***	0.01 (0.01)	0.001 (0.01)	–0.008 (0.003)**	–0.04 (0.01)***	–0.05 (0.01)***
% of area in public land (5)	–0.12 (0.41)	–0.49 (0.73)	–0.61 (0.62)	–0.39 (0.21)*	0.76 (0.38)**	0.36 (0.32)	–0.56 (0.233)**	0.51 (0.30)*	–0.05 (0.21)
In metro county (6)	–0.32 (0.41)	–0.597 (0.61)	–0.92 (0.48)*	–0.31 (0.21)	0.38 (0.31)	0.07 (0.24)	0.296 (0.219)	–0.43 (0.30)	–0.13 (0.23)
N	799			799			1,202		
$\hat{\lambda}$ (SEM)	0.26 (0.07)***			0.19 (0.11)*			0.259 (0.03)***		
Model	SEM			SEM			SEM		

Notes: For a given class and decade, $\hat{\beta}_p$ indicates the average impact of variable *p* on agricultural cover change in matched control areas, $\hat{\gamma}_p$ indicates the average incremental impact of variable *p* on agricultural cover change due to treatment, and $\hat{\beta}_p + \hat{\gamma}_p$ indicates the (total) average impact of variable *p* on agricultural cover change in CH polygons (equation 8). Developed lot price and cropland cost are in $10,000/acre units. All regression models include dummy variables for each FWS region. In the spatial error model (SEM), the weight matrix is given by the normalized inverse matrix of Euclidean distances between observations. Distances are measured from the centroids of polygons. $\hat{\lambda}$ is the estimated SEM coefficient associated with the spatially correlated errors. The spatial regressions were done with the STATA ADO files spatwmat, spatdiag, and spatreg. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

Table 11. The Effects of Economic and Land Availability Characteristics on Percentage Change in Seminatural (SN) Land Use Area

Class	'92						'01		
Decade	92–01			01–11			01–11		
Variable (p)	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}+\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}+\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}+\hat{\gamma}$
Constant (0)	–0.15 (0.84)	–0.92 (0.85)	–1.07 (1.04)	–3.27 (1.42)**	6.03 (1.26)***	2.75 (1.72)	–1.16 (1.01)	0.96 (0.77)	–0.20 (0.98)
Developed lot price (1)	–0.001 (0.03)	0.02 (0.05)	0.02 (0.04)	0.06 (0.04)	0.05 (0.07)	0.11 (0.06)*	0.03 (0.04)	–0.06 (0.04)	–0.03 (0.03)
Cropland cost (2)	2.12 (2.78)	–17.41 (6.28)***	–15.28 (5.79)***	–10.37 (4.10)**	–22.28 (9.27)**	–32.64 (8.59)***	–1.90 (3.20)	–7.62 (4.07)**	–9.52 (2.85)***
% of area in dev. at beginning of decade (3)	–0.01 (0.01)	–0.01 (0.02)	–0.02 (0.02)	0.01 (0.02)	–0.01 (0.04)	–0.005 (0.03)	–0.005 (0.018)	0.029 (0.025)	0.02 (0.02)
% of area in ag. at beginning of decade (4)	–0.01 (0.01)	0.12 (0.02)***	0.11 (0.02)***	0.03 (0.01)**	–0.06 (0.03)**	–0.03 (0.03)	0.012 (0.01)	0.05 (0.03)**	0.06 (0.02)***
% of area in public land (5)	–0.27 (0.50)	2.51 (0.95)***	2.23 (0.83)***	1.63 (0.74)**	–6.95 (1.41)***	–5.32 (1.25)***	0.90 (0.68)	–0.76 (0.91)	0.14 (0.64)
In metro county (6)	0.13 (0.50)	–0.30 (0.86)	–0.17 (0.75)	–0.432 (0.736)	2.98 (1.29)**	2.55 (1.14)**	–0.61 (0.64)	1.22 (0.905)	0.61 (0.70)
N	799			799			1,202		
$\hat{\lambda}$ (SEM)	0.71 (0.04)***			0.77 (0.04)***			0.46 (0.06)***		
Model	SEM			SEM			SEM		

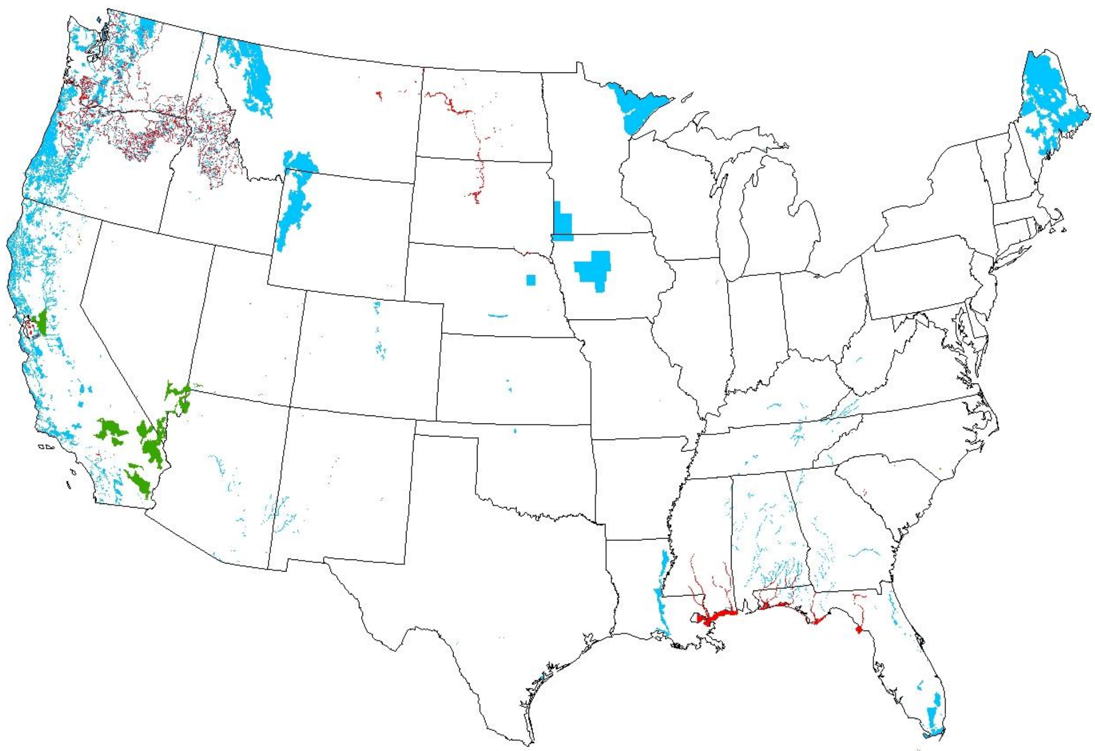
Notes: For a given class and decade, $\hat{\beta}_p$ indicates the average impact of variable p on SN cover change in matched control areas, $\hat{\gamma}_p$ indicates the average incremental impact of variable p on SN cover change due to treatment, and $\hat{\beta}_p+\hat{\gamma}_p$ indicates the (total) average impact of variable p on SN cover change in CH polygons (equation 8). Developed lot price and cropland cost are in $10,000/acre units. All regression models include dummy variables for each FWS region. In the spatial error model (SEM), the weight matrix is given by the normalized inverse matrix of Euclidean distances between observations. Distances are measured from the centroids of polygons. $\hat{\lambda}$ is the estimated SEM coefficient associated with the spatially correlated errors. The spatial regressions were done with the STATA ADO files spatwmat, spatdiag, and spatreg. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

Table 12. Economic Cost Estimates of CH Designation on Development from Published Economic Analyses (EA) and Our Treatment Effects

Species		Costs (in thousands of 2010$)			
Common name (used in FR notice)	Scientific name	EA: total annual costs	EA: annual costs to development	Land cover opportunity costs	Average treatment effect
Alameda whipsnake	*Masticophis lateralis euryxanthus*	54,265	54,212	7,258	–1.06%
Puget Sound chinook salmon ESU	*Oncorhynchus tshawytscha*	104,384	413	(1,039)	+0.16%
Lower Columbia River chinook salmon ESU	*Oncorhynchus tshawytscha*	42,112	1,030	(835)	+0.05%
Upper Willamette River chinook salmon ESU	*Oncorhynchus tshawytscha*	36,064	1,832	(553)	+0.11%
Upper Columbia River spring-run chinook salmon ESU	*Oncorhynchus tshawytscha*	19,712	45	795	–0.37%
Hood Canal summer-run chum salmon ESU	*Oncorhynchus keta*	7,952	10	12	–0.01%
Columbia River chum salmon ESU	*Oncorhynchus keta*	19,152	90	695	–0.50%
Ozette Lake sockeye salmon ESU	*Oncorhynchus nerka*	3	0	0	0.0%
Upper Columbia River steelhead ESU	*Oncorhynchus mykiss*	30,352	50	362	–0.13%
Snake River Basin steelhead ESU	*Oncorhynchus mykiss*	33,600	259	7,276	–0.42%
Lower Columbia River steelhead ESU	*Oncorhynchus mykiss*	40,992	964	2,742	–0.61%
Upper Willamette River steelhead ESU	*Oncorhynchus mykiss*	17,024	2,112	(391)	+0.04%
Middle Columbia River steelhead ESU	*Oncorhynchus mykiss*	48,272	116	5,152	–0.30%

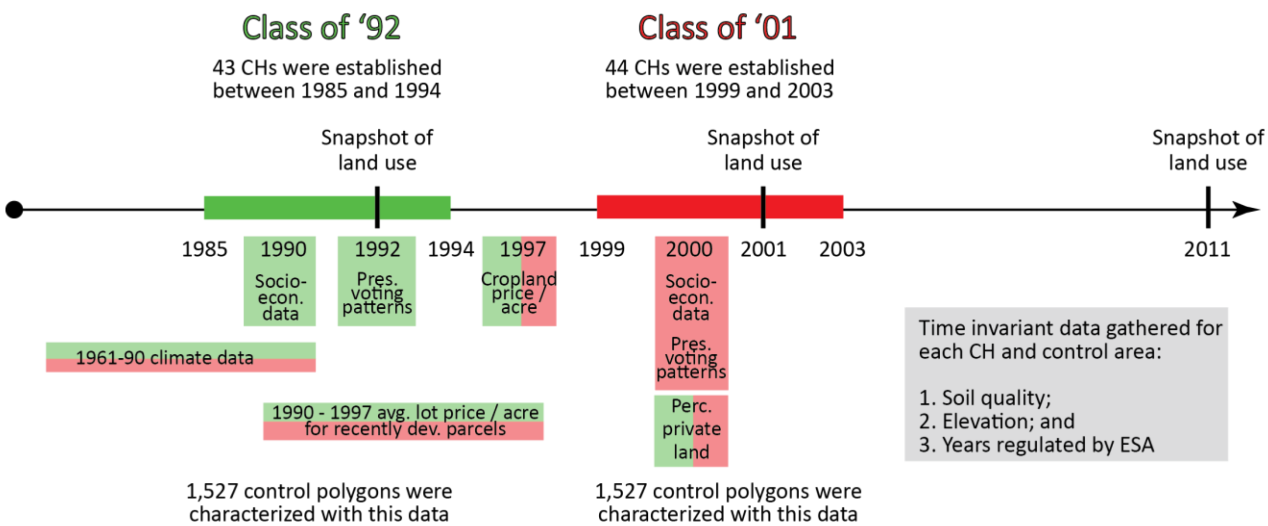
Notes: Annual costs based on a 7% discount rate and converted to 2010$. The average treatment effect for a listed species in this table was the area-weighted average of the difference in development rates in CH polygons compared with matching polygons from 2001 to 2011 (a negative treatment effect means that less development occurred in CH polygons). Our "land cover opportunity costs" due to the treatment effect were calculated on a per-CH polygon basis (Appendix E) and then summed for all CH polygons for a listed species. A negative treatment effect results in positive "cost due to treatment effect"—that is, an opportunity cost of lost development. Negative "costs" are shown in ( ) due to positive treatment effects (greater development rates in CH polygons).

Figure 1. Conterminous US with Designated Critical Habitat Areas for 310 Species, as of 2013



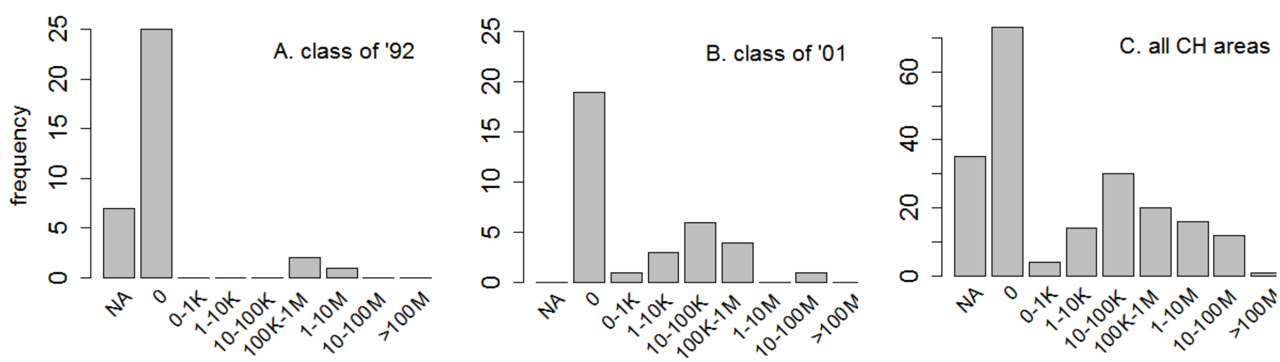
Notes: Green areas are Class of '92 CHs, red areas are Class of '01 CHs, and blue areas are all other CHs. Digital CH shapefiles are available for download from http://ecos.fws.gov/crithab/.

Figure 2. CH Classes and their Covariate Data



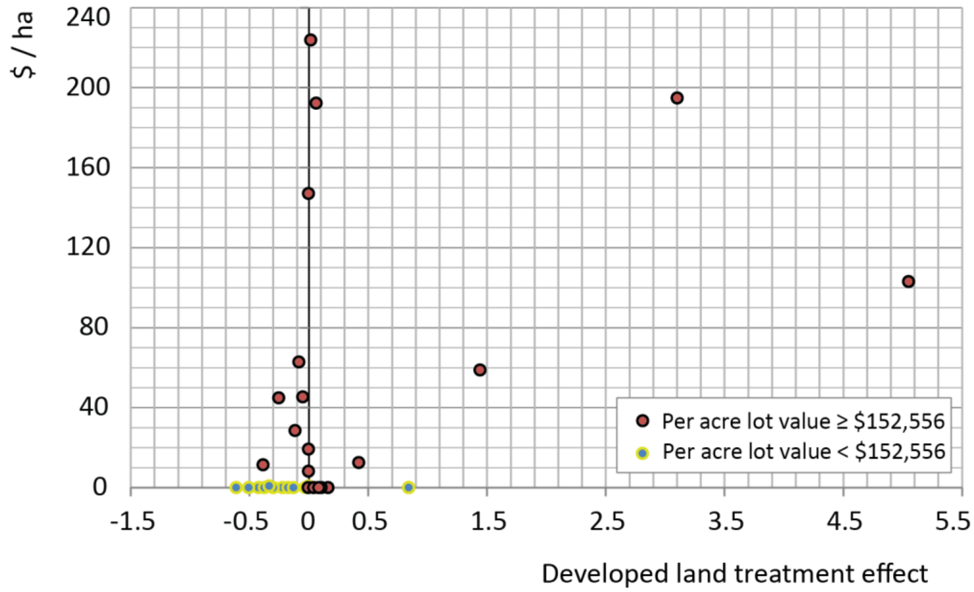
Notes: The covariate vector $\mathbf{x}_{92}$ includes all data shaded in green and gray. The covariate vector $\mathbf{x}_{01}$ includes all data shaded in red and gray. The green and red bars on the timeline indicate the CHs, as identified by year of establishment, that belong to each class.

Figure 3. Histogram of Annualized Cost Estimates for Class of '92, Class of '01, and All CH Areas (2010$)



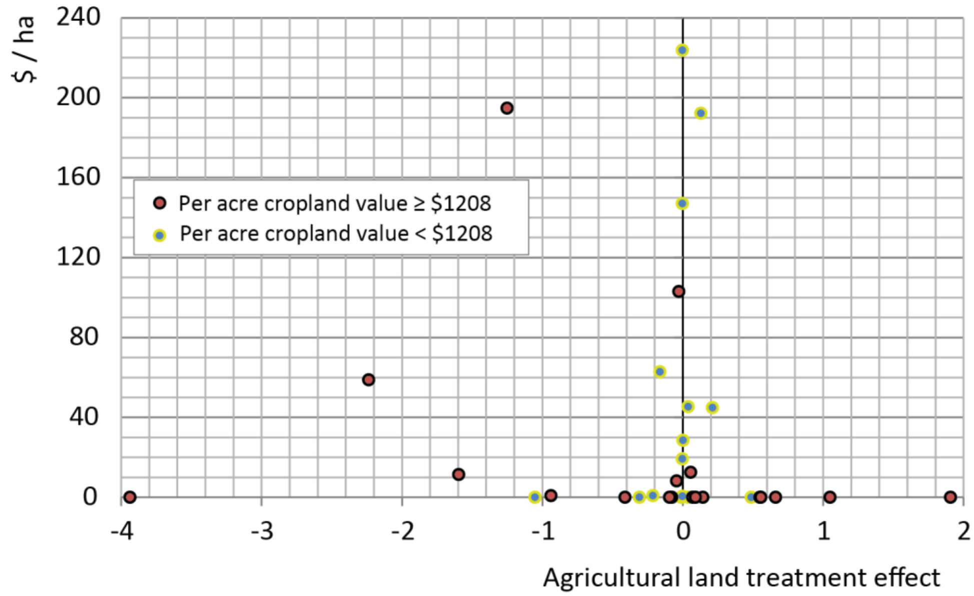
Notes: From economic analyses (EAs) presented in the *Federal Register* with the designation of critical habitat (note change in y-axis scale in Panel C). This summary includes only costs assigned to CH designation; we ignore costs estimated to occur in CH areas but for reasons other than CH designation, such as species listing (we do not include the 15 EAs that do not separate these costs). Many cost estimates were presented as a total over a 10- or 20-year time period. These were annualized using a discount rate of 7% if the FR did not state a specific rate used. It is not clear whether these costs were expected to become 0 at the end of the specified time frame. NA means no cost estimate was provided with CH designation; the 0 category includes species where no formal EA was conducted but statements regarding CH designation such as "no significant economic impacts" or "few additional economic effects" were made. Many EAs provide a low and high cost estimate, and if necessary, we took the midpoint on a logarithmic scale to assign the estimate to a single cost category used here.

Figure 4. Class of ’01 CHs’ Developed Land Treatment Effects vs. Predicted per Hectare Annualized Costs



Notes: Plots are segregated by the CH areas’ average per acre lot value (1990–97 average in 1997$), where $152,556 is the median lot value across all CH areas. Developed land treatment effect in a CH area is given by the area’s 2001–11 change in developed land less the same change across its matches. The matches represented in this figure are from a three-neighbor match, so change in developed land in a CH area’s match is an average over three observations. All Class of ’01 observations in Figure 3 are included here except plot points {ATE, FR Cost/ha} = {–0.077, 558}; {0.000, 29731}; {4.286, 1092}. These three CH areas are not in the plot because their per hectare costs are at least twofold greater than the maximum y-axis value.

Figure 5. Class of '01 CHs' Agricultural Treatment Effects vs. Predicted per Hectare Annualized Costs



Notes: Plots are segregated by the CH areas' average per acre cropland value (in 1997 in 1997$), where $1,208 is the median cropland value across all CH areas. Agricultural treatment effect in a CH area is given by the area's 2001–11 change in agricultural land less the same change across its matches. The matches represented in this figure are from a three-neighbor match, so change in agricultural land in a CH area's match is an average over three observations. All Class of '01 observations in Figure 3 are included here except plot points {ATE, FR Cost/ha} = {–0.200, 558}; {0.097, 29731}; {-0.085, 1092}. These three CH areas are not in the plot because their per hectare costs are at least twofold greater than the maximum y-axis value.

Appendices

Appendix A. Species Used for Matching Analysis Results in Class of ’92 and Class of ’01

Table A.1. Critical Habitat Established 1985–94 (Class of ’92)

Common name	Scientific name (subpop. or status)	CH year
Alabama beach mouse	*Peromyscus polionotus ammobates*	1985
Ash Meadows blazingstar	*Mentzelia leucophylla*	1985
Ash Meadows gumplant	*Grindelia fraxinipratensis*	1985
Ash Meadows ivesia	*Ivesia kingii* var. *eremica*	1985
Ash meadows milk-vetch	*Astragalus phoenix*	1985
Ash Meadows naucorid	*Ambrysus amargosus*	1985
Ash Meadows sunray	*Enceliopsis nudicaulis* var. *corrugate*	1985
Amargosa niterwort	*Nitrophila mohavensis*	1985
Amber darter	*Percina antesella*	1985
Large-flowered fiddleneck	*Amsinckia grandiflora*	1985
Big Spring spinedace	*Lepidomeda mollispinis pratensis*	1985
Conasauga logperch	*Percina jenkinsi*	1985
Desert dace	*Eremichthys acros*	1985
Fresno kangaroo rat	*Dipodomys nitratoides exilis*	1985
Hiko White River springfish	*Crenichthys baileyi grandis*	1985
Modoc sucker	*Catostomus microps*	1985
Navajo sedge	*Carex specuicola*	1985
Niangua darter	*Etheostoma nianguae*	1985
Owens tui chub	*Gila bicolor snyderi*	1985
Spring-loving centaury	*Centaurium namophilum*	1985
Warner sucker	*Catostomus warnerensis*	1985
White River springfish	*Crenichthys baileyi baileyi*	1985
White River spinedace	*Lepidomeda albivallis*	1985
Desert pupfish	*Cyprinodon macularius*	1986
June sucker	*Chasmistes liorus*	1986
Railroad Valley springfish	*Crenichthys nevadae*	1986
Sonora chub	*Gila ditaenia*	1986
Cape Fear shiner	*Notropis mekistocholas*	1987
Heliotrope milk-vetch	*Astragalus montii*	1987
Inyo California towhee	*Pipilo crissalis eremophilus*	1987
Little Colorado spinedace	*Lepidomeda vittata*	1987
Pecos bluntnose shiner	*Notropis simus pecosensis*	1987
Waccamaw silverside	*Menidia extensa*	1987
Welsh’s milkweed	*Asclepias welshii*	1987

Common name	Scientific name (subpop. or status)	CH year
Mount Graham red squirrel	*Tamiasciurus hudsonicus grahamensis*	1990
Rice rat	*Oryzomys palustris* (pop. 3)	1993
Bonytail chub	*Gila elegans*	1994
Colorado pikeminnow (squawfish)	*Ptychocheilus lucius*	1994
Desert tortoise	*Gopherus agassizii* (T)	1994
Delta smelt	*Hypomesus transpacificus*	1994
Humpback chub	*Gila cypha*	1994
Least Bell's vireo	*Vireo bellii pusillus*	1994
Razorback sucker	*Xyrauchen texanus*	1994

Table A.2. Critical Habitat Established 1999–2003 (Class of '01)

Common name	Scientific name (subpop. or status)	CH year
Huachuca water-umbel	*Lilaeopsis schaffneriana* var. *recurva*	1999
Alameda whipsnake (striped racer)	*Masticophis lateralis euryxanthus*	2000
Chinook salmon	*Oncorhynchus tshawytscha* (LowColRiver)	2000
Chinook salmon	*Oncorhynchus tshawytscha* (Puget Sound)	2000
Chinook salmon	*Oncorhynchus tshawytscha* (WA)	2000
Chinook salmon	*Oncorhynchus tshawytscha* (Willamette)	2000
Chum salmon	*Oncorhynchus keta* (OR, WA)	2000
Chum salmon	*Oncorhynchus keta* (WA)	2000
Johnson's seagrass	*Halophila johnsonii*	2000
Sockeye salmon	*Oncorhynchus nerka* (Ozette Lake)	2000
Steelhead	*Oncorhynchus mykiss* (Columbia R.)	2000
Steelhead	*Oncorhynchus mykiss* (OR, WA)	2000
Steelhead	*Oncorhynchus mykiss* (Snake R.)	2000
Steelhead	*Oncorhynchus mykiss* (WA)	2000
Steelhead	*Oncorhynchus mykiss* (Willamette R.)	2000
Virgin River chub	*Gila seminuda*	2000
Woundfin	*Plagopterus argentissimus* (E)	2000
Zapata bladderpod	*Lesquerella thamnophila*	2000
Wenatchee Mountains checkermallow	*Sidalcea oregana* var. *calva*	2001
Morro shoulderband (banded dune) snail	*Helminthoglypta walkeriana*	2001
Piping plover	*Charadrius melodus* (E)	2001
Spruce-fir moss spider	*Microhexura montivaga*	2001
Zayante band-winged grasshopper	*Trimerotropis infantilis*	2001
Spineflower, Scotts Valley	*Chorizanthe robusta* var. *hartwegii*	2001
Appalachian elktoe	*Alasmidonta raveneliana*	2002
Cushenbury milk-vetch	*Astragalus albens*	2002
Carolina heelsplitter	*Lasmigona decorate*	2002
Purple amole	*Chlorogalum purpureum*	2002
Otay tarplant	*Deinandra (Hemizonia) conjugens*	2002
Gaviota tarplant	*Deinandra increscens* ssp. *villosa*	2002
Lompoc yerba santa	*Eriodictyon capitatum*	2002
Cushenbury buckwheat	*Eriogonum ovalifolium* var. *vineum*	2002

Common name	Scientific name (subpop. or status)	CH year
Parish's daisy	*Erigeron parishii*	2002
Santa Cruz tarplant	*Holocarpha macradenia*	2002
San Bernardino Mountains bladderpod	*Lesquerella kingii* ssp. *bernardina*	2002
Cushenbury oxytheca	*Oxytheca parishii* var. *goodmaniana*	2002
Kneeland Prairie penny-cress	*Thlaspi californicum*	2002
San Bernardino Merriam's kangaroo rat	*Dipodomys merriami parvus*	2002
Baker's larkspur	*Delphinium bakeri*	2003
Yellow larkspur	*Delphinium luteum*	2003
Gulf sturgeon	*Acipenser oxyrinchus desotoi*	2003
Rio Grande silvery minnow	*Hybognathus amarus* (E)	2003
Keck's checker-mallow	*Sidalcea keckii*	2003
Scotts Valley polygonum	*Polygonum hickmanii*	2003

Appendix B. Matching Methods

One method for finding a match or matches for each observed $\hat{y}_{1k}$ is to use the Mahalanobis distance, where the character distance between *k* and some *q* is

$$d(\mathbf{x}_q, \mathbf{x}_k) = \left[(\mathbf{x}_q - \mathbf{x}_k)' \boldsymbol{\Sigma}_{\mathbf{x}}^{-1} (\mathbf{x}_q - \mathbf{x}_k)\right]^{0.5} \tag{I}$$

where $\boldsymbol{\Sigma}_{\mathbf{x}}^{-1}$ is the sample *R*×*R* covariance matrix of **x** with length *R* (Glewwe 2014). If we are using a unique match, we assign to $\hat{y}_{1k}$ the $\hat{y}_{0q}$ associated with the $\mathbf{x}_q$ that minimizes $d(\mathbf{x}_q, \mathbf{x}_k)$. If the size of $C(k)$ equals *Z*, we assign to $\hat{y}_{1k}$ the set of $\hat{y}_{0q}$s associated with the $\mathbf{x}_q$s that have the *M* smallest $d(\mathbf{x}_q, \mathbf{x}_k)$ values, where $\alpha_{kq} = 1/M$ for each *q*. Assuming we conduct this matching with replacement, one *q* can be matched to more than one *k*.

We can also use the propensity score to find "counterfactual" outcomes to match with the treated outcomes. If we use the nearest-neighbor match with replacement algorithm, then each *k* is assigned the *q* that minimizes $\|p(\mathbf{x}_q) - p(\mathbf{x}_k)\|$. Again, more than one *k* can be matched with the same *q*. The function p(x) = P[w = 1|**x**] is typically estimated with a probit or logit model.

Once **x** is constructed and $p(\mathbf{x}_q)$ and $p(\mathbf{x}_k)$ are estimated for all *q* and *k*, we may need to throw out the *k* whose minimal norm $\|p(\mathbf{x}_q) - p(\mathbf{x}_k)\|$ is greater than some tolerance level δ to balance the covariates (caliper matching; Cochran and Rubin 1973). In addition, variables that are not well balanced can be improved on this metric by including higher-order terms of the variable or interactions between the covariates in the explanatory variable matrix **x** (guidelines in Caliendo and Kopeinig 2008; Dehejia and Wahba 1999).

Appendix C. Covariates That Can Be Included in the x and S_j Vectors

Covariate category	Data for each polygon on the landscape	Sources
Land cover	For the years 1992, 2001, and 2011: 1. hectares in open water 2. hectares in developed (areas with a mixture of constructed materials and vegetation; ranges from low to high intensity of constructed materials) 3. hectares in barren 4. hectares in forest 5. hectares in grassland/shrub 6. hectares in agriculture 7. hectares in wetlands 8. hectares in other	Fry et al. 2009, 2011; Jin et al. 2013.
Biophysical conditions	9. average elevation (m) 10. 1961–90 and 1990–2009 average annual precipitation (inches) 11. 1961–90 and 1990–2009 monthly average temp (d C) during Dec., Jan., & Feb. 12. percentage of area in land capability classification (LCC) 1–4 (the best) 13. percentage of area in land capability classification (LCC) 5–8 (the worst)	Gesch 2007; Gesch et al. 2002; PRISM Climate Group 2014; Kalnay et al. 1996; Radeloff et al. 2012
Economic conditions	14. 1990 population (people per ha) 15. 2000 population (people per ha) 16. 1990 per capita income (in 1990$) 17. 2000 per capita Income (in 2000$) 18. 1990 jobs per 100 people 19. 2000 jobs per 100 people 20. 1990 wage per job (in 1990$) 21. 2000 wage per job (in 2000$) 22. Lot price per acre for recently developed parcels in host county (1990–97 average) 23. cropland cost in $/acre (1997) 24. whether or not the polygon is in a metropolitan county 25. distance to nearest urban area	National Atlas of the United States 2006; Seirup and Yetman 2006; Seirup et al. 2012; Withey et al. 2012
Political preferences	26. 1992 Clinton votes (votes per ha) 27. 1992 non-Clinton votes (votes per ha) 28. 2000 Gore votes (votes per ha) 29. 2000 non-Gore votes (votes per ha)	Leip 2014
ESA listing	30. first year the area was in one or more listed species' ranges 31. FWS region	NatureServe 2014

The vector $\mathbf{x}_{92}$ includes all of these variables except for data from 1993 and beyond. The vector $\mathbf{x}_{01}$ includes all of these variables except for data from before 2000. When searching for a balanced set of treated areas and matched control polygons, we dropped some variables from the **x** vectors, added transformed version of the covariates n x, or both. For example, in some psmatch2 routines (the STATA code used in this analysis), we added some quadratic or interacted forms of the covariates. Below we list the various covariate vectors we used in this analysis.

Basic model with $\mathbf{x_{92}}$: fraction of polygon in LCCs 1 and 2 (sl12frac); fraction of polygon in LCCs 3 and 4 (sl34frac); average of 1961–90 monthly average temp (d C) during Dec., Jan., & Feb. in polygon (te6190); fraction of polygon in public land (publfrac); average elevation in polygon (elev); polygon population density in 1990 (pop90); polygon average per capita income in 1990 (pcinc90); density of votes for President Clinton in 1992 election in polygon (clinton); area of polygon in water in 1992 (water92); area of polygon in barren cover in 1992 (barren92); area of polygon in forest in 1992 (forest92); area of polygon in grassland in 1992 (grass92); area of polygon in agriculture in 1992 (ag92); area of polygon in wetlands in 1992 (wet92); area of polygon in development in 1992 (dev92); first year the polygon was in one or more listed species (min_year); equals 1 if polygon is in FWS region 1 (fwsdum1); equals 1 if polygon is in FWS region 2 (fwsdum2); equals 1 if polygon is in FWS region 3 (fwsdum3); equals 4 if polygon is in FWS region 4 (fwsdum4); equals 1 if polygon is in FWS region 5 (fwsdum5); equals 1 if polygon is in FWS region 6 (fwsdum6); average lot price per acre for recently developed parcels in polygon (1990–97 average) (urbret); average cropland cost in dollars per acre in polygon in 1997 (crpret); polygon's distance to nearest urban area (urbdist).

Interaction model with $\mathbf{x_{92}}$: sl12frac; sl34frac; te6190; publfrac; elev; pop90; pcinc90; gore; water92; barren92; forest92; grass92; ag92; wet92; dev92; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist; te9009 x 1961–90 average annual precipitation (pretemp); sl12frac x publfrac (soil12pub); pop90 x pcinc90 (pop90inc90); urbdist x min_year (urbdistminyear); fwsdum1 x urbret (fwsdum1urbret); fwsdum2 x urbret (fwsdum2urbret); fwsdum3 x urbret (fwsdum3urbret); fwsdum4 x urbret (fwsdum4urbret); fwsdum5 x urbret (fwsdum5urbret); fwsdum6 x urbret (fwsdum6urbret); dev92 x urbdist (dev92urbdist); ag92 x urbdist (ag92urbdist).

Quadratic model with $\mathbf{x_{92}}$: sl12frac; sl34frac; te6190; publfrac; elev; pop90; pcinc90; clinton; water92; barren92; forest92; grass92; ag92; wet92; dev92; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist; sl12frac^2 (soil122); sl34frac^2 (soil342); publfrac^2 (public2); elev^2 (elev2); pop90^2 (pop902); pcinc90^2 (pcinc902); te61909^2 (te61902); clinton^2 (clinton2); water92^2 (water922); barren92^2 (barren922); forest92^2 (forest922);

grass92^2 (grass922); ag92^2 (ag922); wet92^2 (wet922); dev92^2 (dev922); min_year^2 (minyear2); urbret^2 (urbret2); cropret^2 (cropret2); urbdist^2 (urbdist2).

<u>Parsimonious model with $\mathbf{x_{92}}$</u>: sl12frac; sl34frac; publfrac; pop90; pcinc90; clinton; water92; barren92; forest92; grass92; ag92; wet92; dev92; min_year; urbret; crpret; whether or not the polygon is in a Metropolitan county (metro).

<u>Basic model with $\mathbf{x_{01}}$</u>: sl12frac; sl34frac; average of 1990–2009 monthly average temp (d C) during Dec., Jan., & Feb. in polygon (te9009); publfrac; elev; polygon population density in 2000 (pop00); polygon average per capita income in 2000 (pcinc00); density of votes for Gore in 2000 election in polygon (gore); area of polygon in water in 2001 (water0101); area of polygon in barren cover in 2001 (barren0101); area of polygon in forest in 2001 (forest0101); area of polygon in grassland in 2001 (grass0101); area of polygon in agriculture in 2001 (ag0101); area of polygon in wetlands in 2001 (wet0101); area of polygon in development in 2001 (dev0101); min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; crpret; urbdist.

<u>Interaction model with $\mathbf{x_{01}}$</u>: sl12frac; sl34frac; te9009; publfrac; elev; pop00; pcinc00; gore; water0101; barren0101; forest0101; grass0101; ag0101; wet0101; dev0101; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist; te9009 x 1990–2009 average annual precipitation (pretemp); sl12frac x publfrac (soil12pub); pop00 x pcinc00 (pop00inc00); urbdist x min_year (urbdistminyear); fwsdum1 x urbret (fwsdum1urbret); fwsdum2 x urbret (fwsdum2urbret); fwsdum3 x urbret (fwsdum3urbret); fwsdum4 x urbret (fwsdum4urbret); fwsdum5 x urbret (fwsdum5urbret); fwsdum6 x urbret (fwsdum6urbret); dev0101 x urbdist (dev0101urbdist); ag0101 x urbdist (ag0101urbdist).

<u>Quadratic model with $\mathbf{x_{01}}$</u>: sl12frac; sl34frac; te9009; publfrac; elev; pop00; pcinc00; gore; water0101; barren0101; forest0101; grass0101; ag0101; wet0101; dev0101; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist; sl12frac^2 (soil122); sl34frac^2 (soil342); publfrac^2 (public2); elev^2 (elev2); pop00^2 (pop002); pcinc00^2 (pcinc002); te9009^2 (te90092); gore^2 (gore2); water0101^2 (water01012); barren0101^2 (barren01012); forest0101^2 (forest01012); grass0101^2 (grass01012); ag0101^2 (ag01012); wet0101^2 (wet01012); dev0101^2 (dev01012); min_year^2 (minyear2); urbret^2 (urbret2); cropret^2 (cropret2); urbdist^2 (urbdist2).

<u>Parsimonious model with $\mathbf{x_{01}}$</u>: sl12frac; sl34frac; publfrac; pop00; pcinc00; gore; water0101; barren 0101; forest0101; grass0101; ag0101; wet0101; dev0101; min_year; urbret; crpret; metro.

Appendix D. Robustness Checks on Matching

Table D.1. The Difference in Percentage Change in Land Covers of ’92 CH Areas vs. Matched Areas, 1992–2001 and 2001–11, Using Only Covariates That Indicate Land Value

LU	Decade	Matching technique	Avg. treat. effect = treated – controls	Std. error	*t*-stat	Mean bias	CHs on support
D	92–01	No match	–0.03 = 0.21 – 0.23	0.09	–0.33	NA	NA
		No match	–0.04 = 0.21 – 0.24	0.09	–0.43	NA	NA
		4 N, cal. (0.02)	–0.10 = 0.21 – 0.31	0.20	–0.49	4.18	320
		Mahal., cal. (1.5)	0.21 = 0.20 + 0.00	0.19	1.11	0.52	320
	01–11	No match	–0.31 = 0.09 – 0.40	0.15	–2.07**	NA	NA
		No match	–0.25 = 0.09 – 0.35	0.13	–1.99*	NA	NA
		4 N, cal. (0.02)	–0.31 = 0.09 – 0.40	0.26	–1.16	4.18	320
		Mahal., cal. (1.5)	–0.02 = 0.09 – 0.12	0.24	–0.10	0.52	320
A	92–01	No match	0.23 = 0.04 + 0.19	0.22	1.07	NA	NA
		No match	0.28 = 0.04 + 0.24	0.22	1.28	NA	NA
		4 N, cal. (0.02)	0.03 = 0.04 – 0.01	0.38	0.09	4.18	320
		Mahal., cal. (1.5)	–0.26 = 0.12 – 0.38	0.54	–0.48	0.52	320
	01–11	No match	0.40 = 0.14 + 0.26	0.16	2.51***	NA	NA
		No match	0.38 = 0.14 + 0.23	0.16	2.34***	NA	NA
		4 N, cal. (0.02)	0.41 = 0.14 + 0.26	0.27	1.52	4.18	320
		Mahal., cal. (1.5)	0.20 = 0.14 + 0.06	0.29	0.70	0.52	320
SN	92–01	No match	0.38 = 0.20 + 0.17	0.24	1.56	NA	NA
		No match	0.45 = 0.20 + 0.24	0.24	1.87	NA	NA
		4 N, cal. (0.02)	0.63 = 0.21 + 0.43	0.44	1.43	4.18	320
		Mahal., cal. (1.5)	0.47 = 0.14 + 0.34	0.51	0.93	0.52	320
	01–11	No match	1.54 = 1.29 + 0.24	0.28	5.52***	NA	NA
		No match	1.52 = 1.29 + 0.22	0.28	5.50***	NA	NA
		4 N, cal. (0.02)	1.49 = 1.30 + 0.19	0.59	2.51***	4.18	320
		Mahal., cal. (1.5)	1.50 = 1.37 + 0.13	0.67	2.25**	0.54	274

Notes: D = developed, A = agricultural, SN = seminatural. The variables included in this matching analysis are pcinc90, urbret, cropret, urbdist, min_year, and FWS region dummies. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

<u>Basic land value model for 1992</u>: pcinc90; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist.

<u>Interaction land value model for 1992</u>: pcinc90; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist; pop90inc90; urbdistminyear; fwsdum1urbret; fwsdum2urbret; fwsdum3urbret; fwsdum4urbret; fwsdum5urbret; fwsdum6urbret; dev92urbdist; ag92urbdist.

<u>Quadratic model for 1992</u>: pcinc90; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist; pcinc902; minyear2; urbret2; cropret2; urbdist2.

Parsimonious land value model for 1992: pcinc90; min_year; urbret; cropret; metro.

Table D.2. The Difference in Percentage Change in Land Covers of ’01 CH Areas vs. Matched Areas, 2001–11, Using Only Covariates That Indicate Land Value

LU	Matching technique	Avg. treat. effect = treated – controls	Std. error	*t*-stat	Mean bias	CHs on support
D	No match	0.09 = 0.48 – 0.40	0.12	0.74	NA	NA
	No match	0.14 = 0.48 – 0.35	0.11	1.27	NA	NA
	3 N (pars.)	0.16 = 0.48 – 0.33	0.37	0.42	3.16	717
	Mahal., cal. (1) (basic)	0.18 = 0.44 – 0.26	0.72	0.25	0.57	577
A	No match	0.26 = 0.00 + 0.26	0.11	2.38***	NA	NA
	No match	0.24 = 0.00 + 0.23	0.11	2.14**	NA	NA
	3 N (pars.)	0.14 = 0.00 + 0.13	0.23	0.61	3.16	717
	Mahal., cal. (1) (basic)	–0.04 = 0.03 – 0.08	0.31	–0.14	0.57	577
SN	No match	–0.64 = –0.88 + 0.24	0.19	–3.38***	NA	NA
	No match	–0.66 = –0.88 + 0.22	0.19	–3.50***	NA	NA
	3 N (pars.)	–0.65 = –0.88 + 0.23	0.45	–1.44	3.16	717
	Mahal., cal. (1) (basic)	–0.37 = –0.76 + 0.39	0.78	–0.48	0.57	577

Notes: D = developed, A = agricultural, SN = seminatural. The variables included in this matching analysis are pcinc90, urbret, cropret, urbdist, min_year, and FWS region dummies. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

Basic land value model for 2001: pcinc00; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist.

Interaction land value model for 2001: pcinc00; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist; pop00inc00; urbdistminyear; fwsdum1urbret; fwsdum2urbret; fwsdum3urbret; fwsdum4urbret; fwsdum5urbret; fwsdum6urbret; dev0101urbdist; ag0101urbdist.

Quadratic land value model for 2001: pcinc00; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbret; cropret; urbdist; pcinc002; minyear2; urbret2; cropret2; urbdist2.

Parsimonious land value model for 2001: pcinc00; min_year; urbret; cropret; metro.

Table D.3. The Difference in Percentage Change in Land Covers of ’92 CH Areas vs. Matched Areas, 1992–2001 and 2001–11, Using Only Covariates That Indicate Growth

LU	Decade	Matching technique	Avg. treat. effect = treated – controls	Std. error	*t*-stat	Mean bias	CHs on support
D	92–01	No match	–0.04 = 0.21 – 0.24	0.09	–0.43	NA	NA
		No match	–0.03 = 0.21 – 0.23	0.09	–0.33	NA	NA
		4 N, cal. (0.02) (pars.)	–0.01 = 0.21 – 0.21	0.25	–0.02	2.55	322
		Mahal., cal. (1.5) (pars.)	0.06 = 0.21 – 0.15	0.37	0.16	1.12	322
	01–11	No match	–0.31 = 0.09 – 0.40	0.15	–2.07**	NA	NA
		No match	–0.25 = 0.09 – 0.35	0.13	–1.99**	NA	NA
		4 N, cal. (0.02) (pars.)	–0.20 = 0.09 – 0.30	0.19	–1.05	2.55	322
		Mahal., cal. (1.5) (pars.)	–0.05 = 0.09 – 0.14	0.32	–0.15	1.12	322
A	92–01	No match	0.23 = 0.04 + 0.19	0.22	1.07	NA	NA
		No match	0.28 = 0.04 + 0.24	0.22	1.28	NA	NA
		4 N, cal. (0.02) (pars.)	0.08 = 0.04 + 0.03	0.44	0.17	2.55	322
		Mahal., cal. (1.5) (pars.)	–0.22 = 0.04 – 0.27	0.60	–0.37	1.12	322
	01–11	No match	0.40 = 0.14 + 0.26	0.16	2.51**	NA	NA
		No match	0.38 = 0.14 + 0.23	0.16	2.34**	NA	NA
		4 N, cal. (0.02) (pars.)	0.26 = 0.14 + 0.11	0.26	0.98	2.55	322
		4 N, cal. (0.02) (quad.)	0.45 = 0.14 + 0.30	0.23	1.93*	3.61	322
		Mahal., cal. (1.5) (pars.)	0.25 = 0.14 + 0.11	0.33	0.78	1.12	322
SN	92–01	No match	0.38 = 0.20 + 0.17	0.24	1.56	NA	NA
		No match	0.45 = 0.20 + 0.24	0.24	1.87*	NA	NA
		4 N, cal. (0.02) (pars.)	0.55 = 0.20 + 0.34	0.53	1.03	2.55	322
		4 N, cal. (0.02) (quad.)	0.98 = 0.20 + 0.78	0.47	2.09**	3.61	322
		Mahal., cal. (1.5) (pars.)	0.55 = 0.20 + 0.35	0.65	0.85	1.12	322
	01–11	No match	1.54 = 1.29 + 0.24	0.28	5.52***	NA	NA
		No match	1.52 = 1.29 + 0.22	0.28	5.50***	NA	NA
		4 N, cal. (0.02) (pars.)	1.49 = 1.29 + 0.19	0.59	2.53**	2.55	322
		Mahal., cal. (1.5) (pars.)	1.36 = 1.29 + 0.07	0.59	2.30**	1.12	322

Notes: D = developed, A = agricultural, SN = seminatural. The variables included in this matching analysis are 1980–90 growth in per capita income, per capita jobs, per capita wages, and min_year and FWS region dummies. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

<u>Basic growth model for 1992</u>: 1980–90 per capita growth (incgrowth); 1980–90 per capita job growth (jobgrowth); 1980–90 wage growth (wagegrowth); min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbdist.

<u>Interaction growth model for 1992</u>: incgrowth; jobgrowth; wagegrowth; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbdist; jobgrowth x incgrowth (jobinc); incgrowth x urbdist (incurbdist); jobgrowth x urbdist (joburbdist).

<u>Quadratic growth model for 1992</u>: incgrowth; jobgrowth; wagegrowth; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbdist; incgrowth^2 (incgrowth2); jobgrowth^2 (jobgrowth2); wagegrowth^2 (wagegrowth2); urbdist2; min_year2.

<u>Parsimonious growth model for 1992</u>: incgrowth; jobgrowth; wagegrowth; min_year; metro.

Table D.4. The Difference in Percentage Change in Land Covers of '01 CH Areas vs. Matched Areas, 2001–11, Using Only Covariates That Indicate Growth

LU	Matching technique	Avg. treat. effect = treated – controls	Std. error	*t*-stat	Mean bias	CHs on support
D	No match	0.09 = 0.48 – 0.40	0.12	0.74	NA	NA
	No match	0.14 = 0.48 – 0.35	0.11	1.27	NA	NA
	4 N, cal. (0.02) (int.)	0.05 = 0.43 – 0.38	0.19	0.27	2.48	710
	Mahal., cal. (1.5) (pars.)	0.10 = 0.42 – 0.32	0.30	0.34	0.82	689
A	No match	0.26 = 0.00 + 0.26	0.11	2.38**	NA	NA
	No match	0.24 = 0.00 + 0.23	0.11	2.14**	NA	NA
	4 N, cal. (0.02) (int.)	0.00 = 0.00 + 0.00	0.21	0.02	2.48	710
	Mahal., cal. (1.5) (pars.)	0.11 = 0.06 + 0.05	0.35	0.32	0.82	689
SN	No match	–0.64 = –0.88 + 0.24	0.19	–3.38***	NA	NA
	No match	–0.66 = –0.88 + 0.22	0.19	–3.50***	NA	NA
	4 N, cal. (0.02) (int.)	–0.34 = –0.83 + 0.49	0.31	–1.10	2.48	710
	Mahal., cal. (1.5) (pars.)	–0.39 = –0.72 + 0.33	0.42	–0.92	0.82	689

Notes: D = developed, A = agricultural, SN = seminatural. The variables included in this matching analysis are 1990–2000 growth in per capita income, per capita jobs, per capita wages, population, 1992–2001 growth in developed land, and min_year and FWS region dummies. * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.

<u>Basic growth model for 2001</u>: 1990–2000 population growth (popgrowth); 1990–2000 per capita growth (incgrowth); 1990–2000 per capita job growth (jobgrowth); 1990–2000 wage growth (wagegrowth); 1992–2001 developed land growth (devgrowth); min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbdist.

<u>Interaction growth model for 2001</u>: popgrowth; incgrowth; jobgrowth; wagegrowth; devgrowth; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbdist; popgrowth x incgrowth (popinc); popgrowth x jobgrowth (popjob); popgrowth x devgrowth (popdev); jobgrowth x incgrowth (jobinc); devgrowth x incgrowth (devinc); popgrowth x urbdist (popurbdist); incgrowth x urbdist (incurbdist).

<u>Quadratic growth model for 2001</u>: popgrowth; incgrowth; jobgrowth; wagegrowth; devgrowth; min_year; fwsdum1; fwsdum2; fwsdum3; fwsdum4; fwsdum5; fwsdum6; urbdist; popgrowth^2

(popgrowth2); incgrowth^2 (incgrowth2); jobgrowth^2 (jobgrowth2); wagegrowth^2 (wagegrowth2); devgrowth^2 (devgrowth2); urbdist2; min_year2.

Parsimonious growth model for 2001: popgrowth; incgrowth; jobgrowth; wagegrowth; devgrowth; min_year; metro.

Appendix E. Calculating Annual Developed Land Cover Opportunity Cost

For each CH polygon in our Class of '01 cohort (each distinct CH polygon i_k), as well as all control polygons, we estimate percentage change in the area's fraction of developed land cover from 2001 to 2011 (see Section 3). For the purposes of this calculation described below, we used a three-neighbor match, so change in developed land in a CH polygon's match is an average over three observations (as used for treatment effects shown in Figures 4 and 5). The treatment effect for CH polygon i_k is as follows:

Percentage change in fraction of CH polygon i_k in developed land from 2001 to 2011:

> Average percentage change in fraction of control polygon in developed land from 2001 to 2011 across three controls matching CH polygon i_k

To convert this to an annual decay or growth rate k, we use

$$CH(t) = CH_0 e^{kt}$$

where t = 10 (years), CH_0 is CH polygon i_k area, and $CH(t)$ is the "new" area of CH based on the treatment effect. Obviously the CH polygon is not growing or shrinking, but when the treatment effect is negative, k is less than 0, and $CH(t) - CH_0$ can be interpreted as the number of hectares that would have been developed, absent CH designation. When the treatment effect is positive, k is greater than 0, and $CH(t) - CH_0$ is greater than 0 and can be interpreted as the additional number of hectares developed because of the CH designation. Solving for k gives us an annual rate of decay (or growth) to use to calculate an annual developed land cover opportunity cost.

Let the county-specific estimate of lot value over 1990 to 1997, converted to 2010$ and a per hectare value, be given by A_t. A_t is equal to the following:

$$A_t = \sum_{\tau=t+1}^{\infty} \frac{R_t}{(1+r)^{\tau}}$$

where R_t is the annual earnings generated by the hectare developed use in time period t. R_t is also equal to the annual rental value of the hectare in year t. Let us assume that $R_t = R$ for all t. Let us assume t = 0 (hectare is newly developed). Then,

$$A_0 = \sum_{\tau=1}^{\infty} \frac{R}{(1+r)^{\tau}}$$

$$A_0 = R \sum_{\tau=1}^{\infty} \left(\frac{1}{1+r}\right)^{\tau}$$

$$A_0 = R \sum_{\tau=1}^{\infty} \left(\frac{1}{1+r}\right)^{\tau}$$

$$A_0 = R \frac{\frac{1}{1+r}}{1-\frac{1}{1+r}}$$

$$A_0 = R \frac{\frac{1}{1+r}}{\frac{r}{1+r}}$$

$$A_0 = R \frac{1}{1+r} \frac{1+r}{r}$$

$$A_0 = R \frac{1}{r}$$

$$A_0 r = R$$

For our calculation, we use r = 0.07, consistent with the discount rate used in many economic analyses of CH designation published in the *Federal Register*. We then use the R calculated for CH polygon i_k in the following:

$$\text{Annual cost} = (CH_0 e^{k} - CH_0)R$$

The annual costs presented in Table 12 are the sum of "Annual cost" across all CH polygons i_k for species (or ESU) i.