OPERATIONS RESEARCH
Vol. 59, No. 5, September–October 2011, pp. 1059–1078
ISSN 0030-364X | EISSN 1526-5463 | 11 | 5905 | 1059

http://dx.doi.org/10.1287/opre.1110.0961

Dynamic Reserve Selection: Optimal Land Retention with Land-Price Feedbacks

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Urban growth compromises open space and ecosystem functions. To mitigate the negative effects, some agencies use reserve selection models to identify conservation sites for purchase or retention. Existing models assume that conservation has no impact on nearby land prices. We propose a new integer program that relaxes this assumption via adaptive cost coefficients. Our model accounts for the two key land price feedbacks that arise in markets where conservation competes with development: the amenity premium and price increases driven by shifts in market equilibriums. We illustrate the mechanics of the proposed model in a real land retention context. The results suggest that in competitive land markets, the optimal conservation strategy during the initial phase of the retention effort might be to use available dollars to buy fewer parcels with smaller total area that are under high risk of development. We show that failure to capture the land-price feedbacks can lead to significant losses in biological conservation. The present study is the first to create a reserve selection model that captures the economic theory of competitive land markets in a dynamic framework, produces tangible, parcel-level conservation recommendations, and works on problems with thousands of potential site selection decisions and several planning periods.

Subject classifications: integer programming: applications; natural resources: land development.
Area of review: Environment, Energy, and Natural Resources.
History: Received February 2010; revisions received October 2010, January 2011; accepted January 2011.

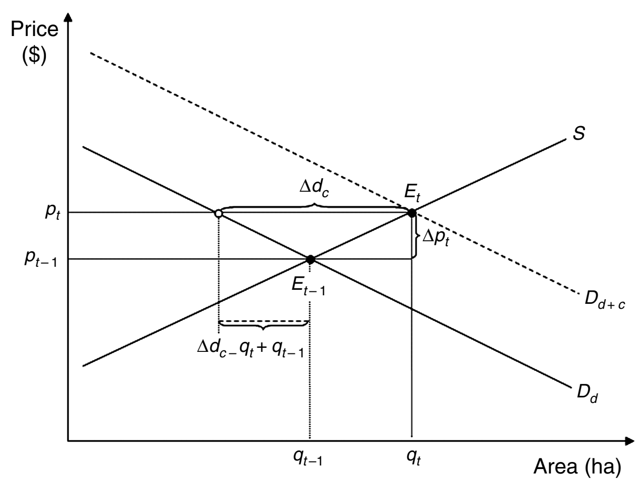
1. Introduction

Urban growth typically reduces the availability of open space near population centers due to the conversion of these lands to real estate or commercial developments. For several decades, this phenomenon has manifested itself in the form of lost biodiversity, recreational opportunities, and other ecosystem services, which in turn triggered widespread efforts of land retention by community planners and conservation organizations. Operations researchers responded by developing decision tools to help planners design market-based incentives or directly acquire land. The operational challenge, central to both strategies (market based or not), has been to prioritize sites for protection given a set of conservation objectives and operational and budgetary constraints.

The initial focus in reserve selection modeling was to ensure a minimum level of representation for some target species at a minimum number of sites (e.g., Margules et al. 1988, Pressey et al. 1997, Possingham et al. 1993, or Underhill et al. 1994), or to maximize species representation within a fixed number of sites (e.g., Camm et al. 1996 or Church et al. 1996). The former minimization problem is equivalent to the set-covering problem (cf. Padberg 1979), a.k.a. the facility location problem (Toregas et al. 1971), whereas the latter maximization problem is known as the maximal species-covering problem in the reserve selection literature (Williams et al. 2005). Species representation models with minimum acquisition costs and maximal representation models with budget constraints are discussed in detail in Ando et al. (1998), Rodrigues et al. (2000), and in ReVelle et al. (2002). Haight et al. (2000), and Camm et al. (2002) captured the probabilistic nature of species occurrence in their respective models. The realization that certain spatial attributes of a reserve network, such as connectivity or shape, can be just as important to the survival of a species as the number of representative populations gave rise to the area of spatial reserve design. Spatially explicit reserve site selection models are characterized by the added combinatorial complexity due to the imbedded network or graph-theoretical constructs that are to ensure, or to best approximate, the desired network features. Examples of connectivity modeling in the reserve selection context include Önal and Briers (2006); compactness is pursued in Tóth and McDill (2008), whereas contiguity is addressed in Tóth et al. (2009). Williams et al. (2005) provide a comprehensive survey of spatial optimization methods applied to reserve design.

A common shortcoming of existing reserve site selection models is the assumption that conservation actions have no impact on the price of land, and therefore on the risk of development, outside the reserves (Armsworth et al. 2006). Empirical data from both the United States (Radeloff et al. 2010) and from Africa and Latin America (Wittemyer et al. 2008) suggest, however, that real estate development pressure is greater in the proximity of reserves. The above assumption is particularly problematic in small coastal or peninsular land markets where strong demand for real estate and conservation meets confined, localized supply. Once a conservation organization enters a market of this kind and starts purchasing land, the competitive equilibrium might shift, leading to higher prices. In the example shown on Figure 1, a hypothetical conservation group buys Δd_c of land in time $t-1$, shifting the demand curve to the right. Without the conservation purchase, the equilibrium price of land would be p_{t-1} and an equilibrium quantity of q_{t-1} of land would be developed. Land to the right of the equilibrium point E_{t-1} would remain as open space. With the conservation acquisition of Δd_c and no additional development, the new equilibrium point E_t would define a new price at p_t. At this price, $q_t - \Delta d_c$ of land would be developed, Δd_c would be preserved, and anything to the right of the new equilibrium would remain open space. Armsworth et al. (2006) argue that if undeveloped open space has the same conservation value as preserved open space, then the conservation acquisition of land in the amount of Δd_c leads to a net gain of only $\Delta d_c - q_t + q_{t-1}$ over what would otherwise remain open space in the absence of conservation actions (Figure 1). In other words, the conservation acquisition of Δd_c comes at the expense of additional open space that is lost to development $(q_t - q_{t-1})$ due to the fact that the conservation-induced price increases (Δp_t) would entice some owners at the margin to sell their land to developers (Armsworth et al. 2006). Depending on the conservation value of this additional open space that is lost relative to that of the newly acquired land, a net loss of biodiversity is possible. This begs the question of what the value of Δd_c should be in a given land market if open space protection is to be maximized subject to budgetary constraints and conservation preferences. The primary contribution of this paper is an operational model that can help community planners answer this question in a spatially and temporally explicit manner.

Figure 1. Conservation-induced change in land prices in a competitive market.



Notes. The horizontal axis is land area available for both conservation and development. D_d is demand for development, and S is supply of land. The demand and supply curves are assumed to be linear near the equilibrium with elasticities of $(\Delta d_c - q_t + q_{t-1})/\Delta p_t = \eta^d$ and $(q_t - q_{t-1})/\Delta d_c = \eta^s$, respectively. At the competitive equilibrium in year $t-1$ (E_{t-1}), area q_{t-1} would be developed. With conservation acquisitions of Δd_c, the competitive equilibrium shifts to E_t in year t leading to a price increase of $\Delta p_t = \delta_c/(\eta^d + \eta^s)$. In the new equilibrium, a total area of q_t would be sold, with Δd_c sold for conservation (Armsworth et al. 2006).

The second contribution is the modeling of a more localized land price feedback, the so-called amenity premium that is induced on lots that are adjacent to the reserves (Thorsnes 2002). Amenity premiums exist because people are willing to pay more for residential lots next to or near designated natural areas (Turner 2005). Again, the concern is that the amenity-driven price increases might trigger unintended losses of open space near the reserves by enticing some landowners to sell their land for real estate (Costello and Polasky 2004, Irwin and Bockstael 2004, McDonald et al. 2007).

The third contribution is the proposed model's capability to account for real estate development that unfolds over time and space, partly as a result of external factors such as the overall state of the housing market, but also as a result of the conservation decisions themselves. The operational significance of accounting for these processes is the assumption that once a land parcel is developed, it cannot be purchased for conservation (Costello and Polasky 2004). Not only the price, but also the availability of land, might change over time as a result of conservation actions. Strategic land retention models must capture these changes in order to provide meaningful recommendations. The proposed integer program incorporates a modified version of Irwin and Bockstael's (2004) hazard model, which was designed to simulate the optimal timing of development. The underlying assumption is that the landowner of parcel i will develop his or her parcel or sell it for development in the first time period t when the net revenues from development (R_{it}) minus the opportunity costs of the undeveloped use (A_{it}) exceed the discounted net returns of developing in the subsequent period plus a random variable θ_{it} (Ineq. 1). Theta accounts for unobservable landowner attributes such as the owner's ties to the land, income, or age (Irwin and

Bockstael's 2002), whereas r denotes the owner's personal discount rate.

$$R_{it} - A_{it} \geqslant (1+r)^{-1} R_{i(t+1)} + \theta_{it}. \tag{1}$$

In addition to land price feedbacks and real estate developments, a third factor that calls for the incorporation of a temporal dimension in reserve selection models is fluctuating budgets. Conservation budgets typically change over time, sometimes rather haphazardly (Meir et al. 2004), due to varying fund performance and the availability of grant dollars or private donations. Therefore, conservation planners should define short-term land retention strategies that best achieve conservation objectives while allowing for maximum flexibility in the subsequent periods (Costello and Polasky 2004, Snyder et al. 2004).

We illustrate the public policy relevance of the proposed dynamic reserve selection model by applying it to a real land market on Lopez Island, Washington (Figure 3). The island's proximity to major population centers such as Seattle gives rise to strong demand for residential properties. At the same time, the island is home to many sensitive or endangered wildlife species and habitat types that are unique to the region (Washington State Department of Fish and Wildlife 2008, Washington State Department of Natural Resources 2009). In 1992–2001 alone, however, an average of nearly 5% of all private forestlands, which is the predominant form of land ownership on the island, was lost to development each year (Bolsinger et al. 1997, Gray et al. 2005). Most of this development has occurred in the most sensitive coastal areas due to popular demand for waterfront properties. The situation is similar across the Puget Sound region: it is estimated that more than 12,000 hectares of forestland are lost each year on average in the area (Bradley et al. 2007). The State of Washington and conservation organizations wish to know how to prioritize their land retention strategies given finite budgets. Should their money be spent on the acquisition of small, expensive parcels that are under high risk of development, or should larger, inexpensive areas that are further away from population centers be pursued instead? Our case study shows that starting the Lopez Island retention effort with fewer, high-risk, high conservation value parcels with less total area would protect more biodiversity. Because the land price feedback effects are driven by the area of conservation acquisitions and by the adjacency between reserved versus unreserved parcels, it makes sense to focus on acres that provide the highest conservation payoffs per dollar expended and per unit of conservation loss unintentionally induced via additional development. Our results from the operational tests on Lopez Island also support the findings of the economic theory of Armsworth et al. (2006) that accounting for conservation-driven land price feedbacks can have a profound impact on optimal retention decisions.

Existing dynamic reserve selection models set a baseline against which the contributions of the present paper can be compared. The pioneering work successfully cast the dynamic reserve selection problem as a stochastic dynamic program in which site availability is uncertain (Costello and Polasky 2004, Strange et al. 2006); however, the authors conclude that finding optimal solutions might be computationally elusive if the number of sites is greater than about 20. Faced with these computational limits, several authors propose heuristic algorithms (Costello and Polasky 2004, Meir et al. 2004, Drechsler 2005, Sabaddin et al. 2007, and Harrison et al. 2008), which are applied to larger problems with hundreds of sites. Finally, Snyder et al. (2004) propose a 0-1 linear programming model that maximizes expected conservation value at the end of a two-period planning horizon given a set of real estate development scenarios. The scenarios were set to materialize only in the second planning period with predefined probabilities that were independent of the conservation decisions in the first period. Applying their model to a 146-site case study, the authors conclude that conservation gains are associated with protecting sites sooner rather than later. Although these modeling achievements are important given the spatiotemporal complexities inherent in dynamic land retention, a knowledge gap remains because none of the models attempt to account for endogenous changes in land price. There is abundant evidence that open space protection decisions affect land price (e.g., Irwin and Bochstael 2004), and those price effects can influence strategic reserve design (Armsworth et al. 2006). The present study is the first to create a reserve selection model that captures the economic theory of competitive land markets in a dynamic framework, produces tangible, parcel-level conservation recommendations, and works on problems with thousands of potential site selection decisions and several planning periods.

2. Model Formulation

This section describes the proposed mixed 0-1 programming model, including guidance on how the required parameters can be estimated in practice. The model maximizes the expected total biodiversity value of land, expressed in biodiversity hectares, in both preserved and undeveloped parcels within a competitive land market. For clarity, the model is introduced in modules, built gradually from a simple core to the full reserve selection model. The following notation was used:

Parameters:

$a_i =$ the area in hectares of parcel i. Source: geographic databases of county tax assessors (e.g., United States) or cadastral surveys (e.g., Europe);

$d_i =$ the biodiversity value of parcel i, measured in biodiversity hectares. In the conservation biology literature, biodiversity value is measured in various ways, including the number of species, communities, or habitat types present weighted by factors such as natural rarity and vulnerability (Margules and Pressey

2000). In our application, the biodiversity value of a parcel is measured by the parcel's *irreplaceability*, or the extent to which parcel development will compromise regional conservation targets for the protection of species and habitats (Margules and Pressey 2000, Meir et al. 2004). We assume that the biodiversity values are constant over time to keep the model simple and to retain the focus on land-price feedback effects. We note, however, that the proposed model structure does not preclude the use of dynamic biodiversity values. Finally, after Armsworth et al. (2006), we assume that biodiversity value is different for preserved versus unpreserved open parcels (see parameter α next). Source: databases of conservation organizations such as The Nature Conservancy, or expert opinion from the field of ecology;

$\alpha =$ a biodiversity correction coefficient for unprotected but undeveloped parcels. A correction is necessary because unprotected parcels, where commercial forestry or other management activities are allowed, might not provide the same conservation value as protected parcels. As an example, some important species persist in old-forest habitat, which might become less available under intensive timber management. Following Armsworth et al. (2006), α is set to take a value within the $[0, 1]$ interval: it is equal to 0 for developed and 1 for protected parcels. Source: expert opinion from the field of ecology;

$I =$ the set of parcels available for conservation or development. Source: real estate websites, databases of conservation organizations, or expert opinion;

$T =$ the set of planning periods ($|T|$ is the length of the planning horizon). Source: decision maker (DM)—the conservation organization or community planner who requests the analysis. The length of the planning horizon in the model primarily depends on the DM's ability to forecast future budget streams. Because reserve selection models can be reoptimized periodically to make use of new information, including new budgets, it is only the parcel selections in the first period that are likely to be implemented by the DM. In addition, as the results of our subsequent analyses suggest, modeling more periods doesn't necessarily change the trends of optimal selections in the first period.

$B_t =$ budget in time period t. Source: decision maker; and

$R_i =$ open space revenues associated with parcel i during the planning horizon. Source: financial analysis of cash flows associated with the activities that take place on parcel i if open space is to be preserved. If these activities are related to forestry, as is the case in the present study, then open space revenues are equal to the *forest value*. The forest value can be calculated using the Faustmann Formula or other techniques. See the textbook of Bettinger et al. (2008) for more details. Similar formulae exist to calculate discounted cash flows for agriculture (see Chapter 7 in Olson 2003).

Variables:

$x_{it} = 1$ if parcel i is selected for conservation acquisition in year t, 0 otherwise ($X = [x_{i,t}]_{|I|\times|T|}$);

$z_{it} = 1$ if parcel i is converted to development in year t, 0 otherwise. Conversion occurs in year t if the real estate value of parcel i (p_{it}) exceeds the net revenues that can be acquired without development (R_i) by at least a predefined margin θ_t. We assume that, unlike real estate values, the open space revenues associated with parcel i (R_i) remain constant in real terms during the planning horizon ($Z = [z_{i,t}]_{|I|\times|T|}$); and

$p_{it} =$ the market value of parcel i in year t. At the beginning of the planning horizon, p_{i1} is equal to the current market value of parcel i. Source of p_{i1}: real estate websites, county assessor's databases.

The model is formulated as follows:

$$f(X, Z) = \text{Max} \sum_i a_i d_i \sum_t x_{it} + \alpha \sum_i a_i d_i \left(1 - \sum_t x_{it} - \sum_t z_{it}\right), \qquad (2)$$

subject to:

$$\sum_t (x_{it} + z_{it}) \leqslant 1 \quad \forall\, i \in I \qquad (3)$$

$$\sum_i p_{it} x_{it} \leqslant B_t \quad \forall\, t \in T \qquad (4)$$

$$x_{it}, z_{it} \in \{0, 1\} \quad \forall\, i \in I, \forall\, t \in T \qquad (5)$$

$$p_{it} \in \mathrm{R}^+ \quad \forall\, i \in I, \forall\, t \in T. \qquad (6)$$

Function (2) maximizes the amount of land in preserved and undeveloped parcels at the end of the planning horizon weighted by each parcel's biodiversity value. Constraint set (3) contains logical constraints that allow a parcel to be either developed or preserved at most once during the planning horizon. This construct assumes that once a land parcel is developed, it will not be available for conservation. Similarly, if the parcel is purchased for conservation, it is assumed to be protected indefinitely. Inequalities (4) are budget constraints: the cost of conservation acquisitions in a given period cannot exceed the associated annual conservation budget. If carry-over of funds between the planning periods is allowed, budget constraints (4) can be replaced with (4′) and (4″), where F_t is a slack variable that represents the amount of unused funds in period t, whereas B'_t is the budget in time period t that includes the unused funds from period $t-1$ compounded by interest rate k. Naturally, $B'_1 = B_1$.

$$\sum_i p_{it} x_{it} + F_t = B'_t \quad \forall\, t \in T, \qquad (4')$$

$$B'_t = F_{t-1}(1+k) + B_t \quad \forall\, t \in \{T \backslash 1\}. \qquad (4'')$$

The nonlinear cross-product term $p_{it}x_{it}$ in constraint set (4) or (4′) may be linearized by replacing $p_{it}x_{it}$ with a continuous variable and adding constraints (13)–(15) to the model (Williams 1999). Alternative linearization methods exist (cf., Adams and Sherali 1990). Finally, constraint set (5) defines the parcel and the development indicator variables as binary, while constraints (6) set the cost variables (p_{it}) to be positive real.

2.1. Modeling Land-Price Feedback Effects

The heart of the model is a pricing apparatus (Equations (7)–(10)) that controls the value of the land prices for each parcel as they transition from one period to the next. We introduce parameter r as the expected annual change in real estate value within the analysis area, e as a one-time amenity premium for a parcel adjacent to at least one protected parcel, η^d and η^s as price elasticities of demand and supply, respectively, for housing development, and y_{it} as a binary variable that takes the value of 1 if and only if at least one parcel that is adjacent to parcel i is selected for conservation in year $t-1$.

$$p_{it} = p_{i(t-1)}[1+(r+qy_{it})] + \frac{a_i}{\eta^d+\eta^s}\sum_{j\in\{I\setminus i\}} a_j x_{j(t-1)} \quad \forall\, i\in I,\ \forall\, t\in\{T\setminus 1\}, \tag{7}$$

$$y_{it}\in\{0,1\} \quad \forall\, i\in I,\ \forall\, t\in\{T\setminus 1\}. \tag{8}$$

The value of y_{it} is set by constraint sets (9) and (10), where S_i denotes the set of parcels that are adjacent to parcel i:

$$\sum_{k\in S_i} x_{k(t-1)} \geqslant y_{it} \quad \forall\, i\in I,\ \forall\, t\in\{T\setminus 1\}, \tag{9}$$

$$\sum_{k\in S_i} x_{k(t-1)} \leqslant |S_i| y_{it} \quad \forall\, i\in I,\ \forall\, t\in\{T\setminus 1\}. \tag{10}$$

Equation (7) calculates the expected market value of each parcel during the planning horizon. The market value in year t will be the sum of (1) the market value of parcel i in the year prior to year t, $p_{i(t-1)}$ compounded by the expected increase (or decrease) in real estate value r as dictated by the general housing market, plus an amenity premium q that is taken into account only if at least one of the parcels that are adjacent to parcel i has been purchased for conservation in year $t-1$ (i.e., if $y_{it}=1$); and (2) a price increase associated with an increased demand for land resulting from the conservation purchases in year $t-1$. The expected short-term appreciation (or depreciation) rate for real estate (r) can be estimated based on recent transaction data in the local market (e.g., Neighborhoodscout 2010), the current economic outlook, and the availability of home ownership incentives. Higher rates of r will likely add to the impact of land-price feedbacks driven by conservation acquisitions.

The area of conservation purchases in year $t-1$ equals $\Delta d_c = \sum_{j\in\{I\setminus i\}} a_j x_{j(t-1)}$, which is the amount by which the demand curve shifts to the right between year $t-1$ and t (Figure 1). Assuming linear demand and supply functions in the neighborhood of the competitive equilibrium with elasticities of η^d and η^s, the change in land price induced by shifting demand can be calculated using basic trigonometry:

$$\Delta p_t = \frac{1}{\eta^d+\eta^s}\sum_{j\in\{I\setminus i\}} a_j x_{j(t-1)}.$$

Again, the nonlinear cross-product term $p_{i(t-1)}y_{it}$ in Equation (7) can be linearized using the same integer programming techniques as in inequality set (4).

Estimation procedures for demand and supply elasticities (η^d, η^s) are available from the land economics literature. For housing demand, economists recommend the use of unitary elasticity ($\eta^d=1$), regardless of price, meaning that a 1% drop in price will induce a roughly 1% increase in demand (see Glennon 1989 or Anderson et al. 1997). For supply elasticities of housing in metropolitan areas, one can use Green et al.'s (2005) extension of Mayer and Somverville's (2000) model. In this model, supply elasticity is estimated by a function of population (n), average transportation cost (k), average house price, cost of capital (l), city growth rate (g), a proportionality factor that is increasing with population density (φ) and income (τ_y) and property taxes (τ_p). For 95 major U.S. metropolitan areas, one can also turn to Saiz (2007) and simply look up the relevant supply elasticities in Table 8. While linear approximations of supply curves are not uncommon in the literature (e.g., Van der Mensbrugghe 2005), the proposed pricing construct (Equation (7)) can easily be extended to incorporate dynamic elasticities via the Green et al. (2005) or Saiz (2007) models if there is concern that nonlinearity might cause erroneous price estimations. As an example, to imbed the Green et al. (2005) elasticity function, one can redefine parameter η^s as an auxiliary variable with time dimension (η^s_t), replace η^s in Inequality (7) and simply add the following linear equation to the model:

$$\eta^s_t = \frac{2}{\varphi\cdot\sqrt{n}}\cdot\frac{(l+\tau_p)(1-\tau_y)-g}{k}\cdot\sum_{i\in I} p_{i(t-1)}/|I|, \tag{7a}$$

where $\sum_{i\in I} p_{i(t-1)}/|I|$ is the average price of a developable parcel in the analysis area in period $t-1$. Using this equation, supply elasticity can change over time as an endogenous function of price. The parameter values (see definitions in the preceding paragraph) can be obtained or estimated by using U.S. census data or local, county, or city databases for tax assessments.

Constraint sets (9)–(10) control the value of binary indicator variable y_{it}. Whereas constraint (9) allows, constraint (10) forces, y_{it} to take the value of one if at least one parcel that is adjacent to parcel i (i.e., one parcel in set S_i) is preserved in year $t-1$. Constraint (10) is necessary because nothing in the objective function would put an upward pressure on the value of y_{it} if $\sum_{k\in S_i} x_{k(t-1)}$ was to be greater than or equal to one. In other words, y_{it}

could remain zero in the absence of constraint (10) and the desired amenity trigger mechanism would fail. We note that a tighter but less parsimonious alternative to constraint set (10) exists:

$$x_{k(t-1)} \leqslant y_{it} \quad \forall\, k \in S_i,\ \forall\, i \in I,\ \forall\, t \in \{T \backslash 1\}. \tag{10'}$$

Figure 2 illustrates the mechanics of constraints (9) and (10) for an existing waterfront property on Lopez Island, Washington.

The calculation of amenity premiums as a function of the adjacency between developable versus preserved lots is based on Thorsnes (2002). For the Grand Rapids, Michigan metropolitan area, the author reports empirical results that imply significant (19%–35%) market value premiums only for residential lots that bordered preserves. The amenity effects in the study appeared to be "highly localized," meaning that in lots that did not share a common boundary with a preserve, the sale-price premiums were hardly, if at all, detectable. The author acknowledges that the extraordinarily steep sale-price gradient might reflect the lack of forest views from lots that are not directly adjacent to the preserves. Although the topographical similarities between our case study site on Lopez Island and the Grand Rapids area prompted us to incorporate Thorsnes' (2002) adjacency-driven empirical results in our optimization model, we note that proximity- or view-based premiums can also be captured by redefining sets S_i ($\forall\, i \in I$) in constraints (9) and (10). To this end, we point out that Tyrväinen and Miettinen (2000) report a much more gradual inverse correlation between the market prices of dwelling sites and their proximity to designated forest preserves in the Salo, Finland area. Those authors show that a view onto the forested areas was a driving factor behind the amenity premiums. Other potential refinements of the amenity construct proposed in constraints (9) and (10) could include accounting for the combined amenity effects of multiple preserves that border the same residential lot. For example, constraints (9) and (10) could be replaced with

$$y_{it} = \frac{\sum_{k\in S_i}(b_{ik}x_{k(t-1)})}{\sum_{k\in S_i} b_{ik}} \tag{9'}$$

where b_{ik} is the length of common boundary between parcels i and k. Although it is possible that the lengths of the shared boundaries between protected and residential lots are better predictors of amenity premiums than the binary adjacency relationships, currently there is no empirical data to support a more sophisticated amenity mechanism in the optimization model.

Lastly, we mention that an alternative adjacency-based amenity trigger can be formulated by reversing the logic behind constraints (9) and (10). In inequality (10″), whenever a parcel is purchased for conservation, the amenity indicators for the adjacent parcels are turned on in the next period:

$$|S_i| x_{it} \leqslant \sum_{k\in S_i} y_{k(t+1)} \quad \forall\, i \in I,\ \forall\, t \in \{T \backslash |T|\}. \tag{10''}$$

Figure 2. Adjacency-based amenity effects can be captured by linear inequalities.

Notes. As an example, the market value of Parcel 28-11495 is compounded by an amenity premium in time period t if either Parcel 28-8711 or 28-2864 is retained as a forest preserve in period $t-1$. The following pair of inequalities demonstrate the logic behind the amenity indicator variable Y_{it}: $x_{28\text{-}8711(1)} + x_{28\text{-}2864(1)} \geqslant Y_{28\text{-}11495(2)}$, $x_{28\text{-}8711(1)} + x_{28\text{-}2864(1)} \leqslant 2Y_{28\text{-}11495(2)}$.

Because the objective function of the proposed model (Equation (2)) provides a downward pressure on the amenity variables, meaning that the $y_{k(t+1)}$ s (for all $k \in S_i$) will take the value of zero if $x_{it} = 0$, each constraint in set (10″) will behave the same way as the corresponding pairs of constraints in sets (9) and (10). While this means that the number of constraints of types (9) and (10) can be cut in half by using constraints (10″), our preliminary tests inferred no computational benefits associated with this move in terms of solution times. We present constraint set (10″) as an alternative in situations where the number of allowable rows in the input coefficient matrix is limited by the integer programming solver at hand.

2.2. Modeling Land Development

To capture the logic in Equation (1) (Irwin and Bockstael 2004) regarding development hazards, we define θ_{it} as a parameter (US$/ha) that accounts for unobservable landowner attributes such as age or ethnicity that might have an impact on the development of parcel i in period t. Theta (θ_{it}) is used in the model as a cutoff value; a dollar amount by which the market value of parcel i (p_{it}) must exceed its open space value (R_i) in period t before the parcel is considered developed by the model. We add the following pair of constraints:

$$p_{it} \geqslant (R_i + \theta_{it}) z_{it} \quad \forall\, i \in I,\ \forall\, t \in T, \tag{11}$$

$$\left(1 - \sum_{t'=1}^{t} z_{it'} - \sum_{t'=1}^{t} x_{it'}\right)(R_i + \theta_{it} - p_{it}) \geqslant 0 \quad \forall\, i \in I,\ \forall\, t \in T. \tag{12}$$

Constraint pairs (11)–(12) set the value of the development indicator variable z_{it} ($\forall\, i \in I$ and $\forall\, t \in T$). Variable z_{it} takes the value of one (i.e., parcel i gets developed in period t) if and only if the following two conditions hold. First, the real estate value of parcel i exceeds the net revenues that can be acquired without development (R_i) by at least a predefined margin of θ_{it} in period t. Second, the parcel is not purchased for conservation or for development prior to or in year t. Whereas constraint (11) allows, constraint (12) forces, z_{it} to take the value of one if the above two conditions hold.

2.3. Linearization

There are three sets of nonlinearities in the model that result from the use of the adaptive price coefficient p_{it}: one occurs in constraint sets (4) and (12), $p_{it}x_{it'}$; one in constraint set (7), $p_{i(t-1)}y_{it}$; and another one in constraint set (12), $p_{it}z_{it'}$. To avoid computational difficulties that are associated with nonlinear 0-1 programs, all three cross-product terms are replaced by continuous variables. As an example, $\varepsilon_{itt'}$ replaces $p_{it}x_{it'}$, where $\varepsilon_{itt'}$ takes the value of 0 if $x_{it'} = 0$, and it is equal to p_{it} if $x_{it'} = 1$. To enforce these logical conditions, we let M denote the maximum value that the price coefficients can take, and borrow the following three linear constraint sets from Williams (1999, p. 164):

$$\varepsilon_{itt'} - Mx_{it'} \leqslant 0 \quad \forall\, i \in I,\ \forall\, t, t' \in T, \tag{13}$$

$$\varepsilon_{itt'} \leqslant p_{it} \quad \forall\, i \in I,\ \forall\, t, t' \in T, \tag{14}$$

$$p_{it} - \varepsilon_{itt'} + Mx_{it'} \leqslant M \quad \forall\, i \in I,\ \forall\, t, t' \in T. \tag{15}$$

The linearization of terms $p_{i(t-1)}y_{it}$ and $p_{it}z_{it'}$ uses the same technique.

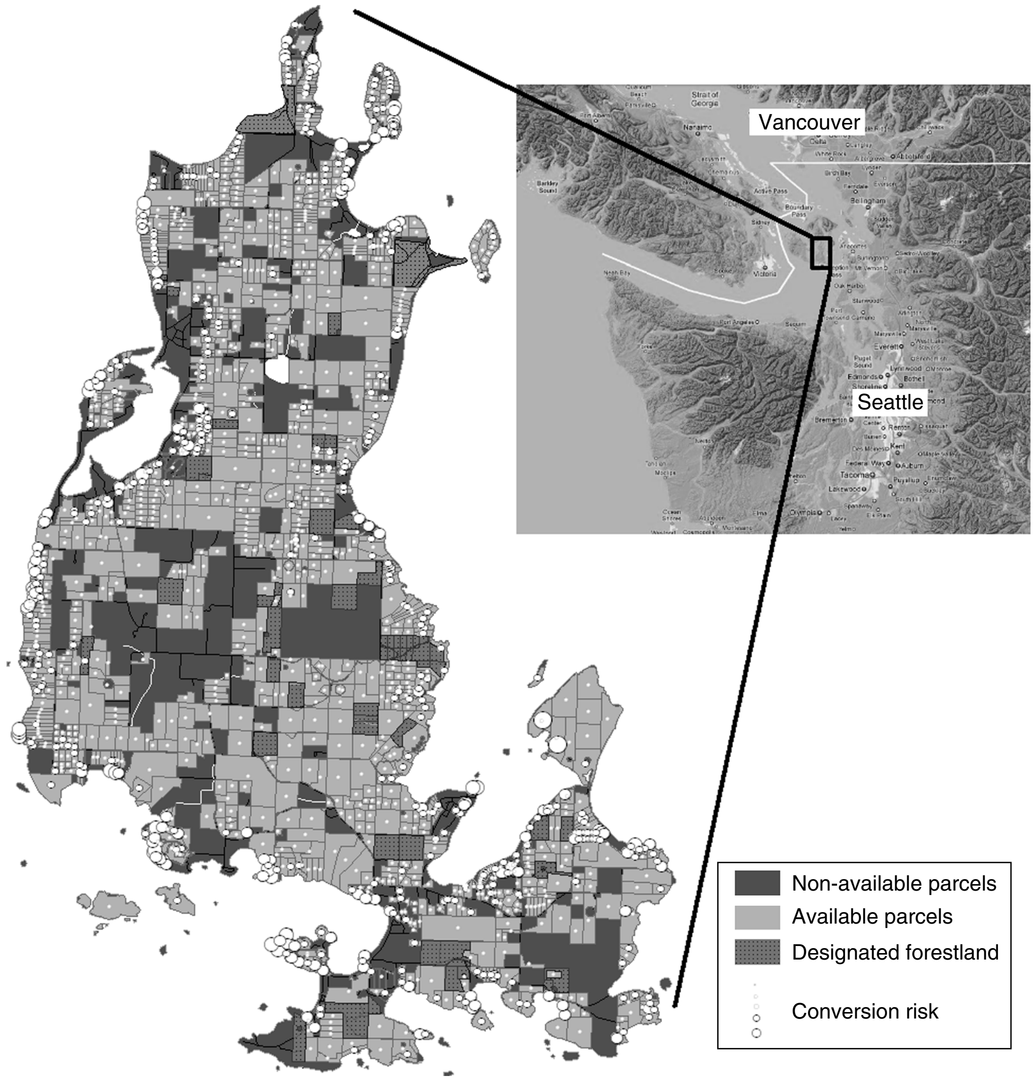
3. Case Study

The optimization model introduced in §2 was applied to a real land market on Lopez Island, Washington. The policy implications of the case study are specific to the study site and apply only under a set of assumptions that are listed below.

3.1. Assumptions

As described in the introduction, Lopez Island (Figure 3) has a competitive land market where both conservation and development are in high demand. We assumed that the island was isolated and unique in both the economic and the ecological sense: the land parcels that we considered had no substitutes either for development or for conservation elsewhere in the San Juan Archipelago. Although this assumption is a departure from reality and it magnifies the competitive nature of the island's land market, it is not a significant one because the island group itself is relatively small and unique. Moreover, the competitive bias is eliminated to a large degree by running the reserve selection model under different supply-demand scenarios, some of which mimic less-competitive markets by using more elastic supply curves. Another simplifying assumption was to model the island as a single land market. Although arguably waterfront properties and interior lots constitute separate markets, or even finer scale partitioning might be possible in theory, we modeled them as a singular market due to insufficient data to characterize the respective equilibriums. If the price elasticities of supply for real estate are known for all submarkets, then this information can be incorporated in the optimization model via Equation (7). The only caveat is that the elasticity parameters or variables would have to be indexed based on the set of parcels with which they are associated. If variable elasticties are used, then separate elasticity functions must be defined for each submarket. We also assumed that the demand curves were linear and the supply curves were linear in the proximity of the equilibriums. Again, if supply elasticity cannot be assumed to be constant, then imbedding an explicit elasticity function such as Equation (7a) in the model is necessary.

Figure 3. Lopez Island, the demonstration site, is located in the Puget Sound region roughly halfway between Seattle, United States, and Vancouver, Canada.



Notes. The light gray polygons are private forest parcels that are assumed to be available for both development and conservation. The white circles represent the conversion risks associated with each parcel. Bigger circles indicate higher risks. The US$ amount by which the market value of a parcel exceeds its forest value was used as a proxy for conversion risk.

3.2. Parcel Data

The Washington State Digital Parcel Database (University of Washington Geographic Information Service, or WAGIS 2009) was used as the primary data source for the model. The database classifies 74.3% of the 7,721-hectare island as private land that comprises either partially forested parcels or designated forestlands. Of the 1,474 parcels that constitute this 74.3% land area, 5 are in "conservation" ownerships and 45 are enrolled in the Washington State Legislature's Designated Forestlands Program under Chapter 84.33 of the Revised Code of Washington (Washington State Legislature 2009). Designated forestlands are taxed based on bare land values for growing and harvesting timber rather than on financially more lucrative land uses such as real estate. To qualify for taxation under the program, the property must be used exclusively for forest management; otherwise, the owner faces penalties and back taxes. For the purposes of the case study, both designated forestlands and the parcels that are in conservation ownerships were removed from the model because they were assumed to be safe from development. An additional 29 parcels, mostly in designated agricultural or recreational categories, were also removed for similar reasons. The remaining 1,395 parcels (4,913.48 ha), each of which was at least 0.5 ha in size with a minimum of 0.25 ha forest cover, were assumed to be available for either conservation or real estate development. Although in reality only a few parcels would be on the market at any time and open space retention is often an opportunistic endeavor, we believe that this assumption is reasonable given the purpose of our analysis. To illustrate the proposed reserve selection model as a device to find optimal land prioritization strategies in competitive markets and to address the question of whether high-risk parcels should be targeted first, we used a set of candidate sites (1,395 parcels) in the analysis that was larger than what the market would typically supply. The model can help us identify guiding principles in general parcel attributes such as conversion risk, biodiversity, or market value, for targeting sites in the smaller sets that become available over time in reality, only if a sufficiently large set is used for the analysis.

3.3. Economic Data

We assumed that forest management and real estate development were the two land use options that maximized the landowners' financial returns on Lopez Island. The current (2007) market values of the parcels (the p_{i0} s) were obtained from county assessors. The open-space values of the parcels (R_i) were assumed to be equal to the working forest values, which in turn were calculated in the database as the sum of bare land values for producing timber plus the value of standing timber in the parcel. The National Land Cover Data Set (U.S. Geological Survey 2007) was used to estimate the area of forest cover within each parcel. Because site-specific forest inventory data were not available, it was assumed that all forest stands were in the midpoint of their rotations. The site index and ownership type of the parcels as well as the area of riparian buffers versus upland areas, which are subject to different sets of management restrictions, were all inputs in the calculation of forest values (WAGIS 2009). In this study, the unit area market value minus the unit area forest value was used as a proxy for conversion risk. We assumed that greater gaps between the two values implied greater development risks.

To fully populate the constraints that account for real estate development in the model, namely constraints (11)–(12), parameter θ_{it} had to be defined. Using the United States Forest Service's most recent forest inventory analysis data for San Juan County (Gray et al. 2005, Bolsinger et al. 1997), we first calculated the average annual rate of private forest loss between 1992 and 2001. We then assumed that the resulting rate of 4.88% was a good approximation for Lopez Island because it is part of San Juan County, for which the rate was derived. We further assumed that this average rate of forest loss would continue to be the trend during the three-year retention period that was to be considered by the model. Finally, we ranked the parcels based on their associated conversion risks from highest to lowest and identified a threshold risk above which the combined area of the parcels just exceeded 4.88% of the total analysis area (4,913.48 ha). Assuming that the parcels with the highest conversion risks would be developed first, we set θ_{it} for each of the 1,395 parcels to be equal to this threshold risk in the first period. After accounting for the conversion losses in the first period, we repeated the above process for the second, and then for the rest of the periods. This a priori definition of θ_{it}s implies that the development of some parcels during the three-year planning horizon is predefined via constraints (11) and (12). The land-price feedbacks captured in Equation (7) determine, however, which of the parcels that have an initial conversion risk below the threshold would get developed in period 2 or 3. Although we recognize the probabilistic nature of land conversions and understand that assigning random values drawn from arbitrarily defined distributions to the θ_{it}s is certainly an option, we believe that the above procedure better reflects what we know about land development in San Juan County.

The expected annual rate of growth in real estate value (r) was assumed to be 3% for the case study. Whereas the annual appreciation rate was 4.42% over the last two years on Lopez Island, it was only 0.49% during the last 12 months and it was −2.64% during the latest quarter (NeighborhoodScout 2010). The 3% near-future rate is an optimistic expectation that takes into account the U.S. Federal Government's 2010 First-Time Homebuyer Credit (U.S. Internal Revenue Service 2010). The one-time amenity premium (q) was set to be either zero, 3%, or 27%, depending on the particular modeling run. If the model was to represent retention efforts that ignored the land-price feedbacks, then the amenity premium was set to zero. Otherwise, it was set to 3% or 27% representing a very modest versus a more moderate amenity scenario. The 27% corresponds to the midpoint within the empirical 19%–35% range that was found to be representative in the Grand Rapids area by Thorsnes (2002). Lastly, to fully account for the spatial nature of the amenity feedbacks, the sets of parcels that were adjacent to each parcel $i \in I$ (denoted by sets S_i) were enumerated using a parcel adjacency matrix generated by standard Arc 9.3 routines (Environmental Systems Research Institute, Inc. 2008).

3.4. Biological Data

The biodiversity coefficient of each parcel (d_i) measures its irreplaceability, or the extent to which parcel development will compromise regional conservation targets for the protection of species and habitats. We determined parcel irreplaceability based on an analysis of biodiversity pattern in Washington State conducted by The Nature Conservancy (TNC) using Washington State Department of Fish and Wildlife's (2008) Priority Habitats and Species Digital Data and plant occurrence information from the Washington Natural Heritage Program (Washington Department of Natural Resources 2009). TNC subdivided Washington State into 728 ha hexagons and determined the importance of each hexagon for protecting species and habitats. We assigned each parcel the irreplaceability value of the hexagon with which it was overlapping. If a parcel overlapped with more than one hexagon, then the average irreplaceability of the hexagons, weighed by the areas of the respective overlaps was used. Because the size of the hexagons (728 ha) was much greater than the average size of the candidate parcels (3.5 ha), the above assignment process may not accurately reflect irreplaceability at the parcel level. As an example, a bald eagle's nest in one corner of a hexagon will not only contribute to the high irreplaceability value of the hexagon itself, but it will also lead to higher values for all the overlapping parcels, including those that are far away from the nest. Although constructing higher-resolution coefficients for biodiversity using the Washington State Department of Fish and Wildlife's (2008) and the Department of Natural Resources' (2009) original data sets is an option, such an effort is beyond the scope of the present study. Another reason for using the lower-resolution irreplaceability data was that results based on the higher-resolution data could not be shared with the public due to the sensitive nature of the information.

The last piece in the puzzle of assembling the input data set was the definition of α, the biodiversity correction coefficient (Armsworth et al. 2006) for unprotected open parcels. Because forest management appears to be the most profitable alternative to real estate development on Lopez Island, we assumed that unprotected open parcels were in the state of working forests. Following the Armsworth et al. (2006) argument that unprotected sites, including working forests, can harbor biodiversity as long as they are not converted to development, we first set α to be equal to 0.8. Our intention was to imply that working forests are dramatically more valuable for biodiversity conservation than housing lots, but not quite as valuable as forest preserves where timber operations are not permitted. Recognizing that the optimal parcel attributes might be sensitive to α, we ran a sensitivity analysis over the settings of 0, 0.1, 0.2, 0.4, 0.6, and 1.0 in addition to the 0.8.

3.5. The Design of the Experiment

To illustrate the use of the proposed optimization model and to provide a glimpse of what the model can do to aid conservation planning and policy, we set up two series of modeling runs for Lopez Island (Table 1). In one series, labeled "Naïve Purchases" (Table 1), the feedback effects were ignored in the parcel selection decisions. In the other series, called "Smart Purchases," the feedbacks were accounted for using the modeling structure described in the Model Formulation section. In the "Naïve Purchases" series, we formulated one model for each of the three budget levels. In the "Smart Purchases" series, we had six models for each of the three annual budget levels that we considered: US$1, US$10, and US$20 million. The US$1 million level was defined based on our understanding of what a realistic budget constraint in the region might look like, whereas the other two scenarios were created to contrast what could be done if more money were available. Under each budget scenario, supply elasticity (η^s) was varied between 1, 0.36, and 0 to simulate increasingly competitive land markets. Steeper, more inelastic supply curves imply that the availability of land for development or for conservation is more limited. Consequently, more inelastic supply curves lead to stronger land-price feedbacks for conservation acquisitions. As an example, land prices would be assumed to go up by US$750/ha at $\eta^s = 1$ versus US$1,100/ha at $\eta^s = 0.36$ and US$1,500/ha at $\eta^s = 0$ on Lopez Island in period t as a result of a 1,500 ha conservation acquisition in period $t-1$ not accounting for price changes due to the general growth in the housing market and amenity premiums. The three values for supply (in)elasticity were chosen to assess the sensitivity of optimal parcel attributes to different levels of competition in the land market. Although the proximity of the Seattle-Bellevue-Everett metro, for which a supply elasticity of 0.78 has been documented in Saiz (2007), has a huge impact on the land market of the study area, we felt that applying this figure in our model was simplistic given the unique nature of the Lopez Island market. Located just outside of the Seattle metro in the middle of the scenic Puget Sound, the housing market on Lopez Island is more akin to resort markets than to urban markets. Because the Saiz (2007) model was designed for urban areas and we found no data on resort markets, we decided to do a simple sensitivity analysis for supply elasticity. Lastly, after Glennon (1989), the demand curves for housing were assumed to have constant unitary elasticities in each of the modeling runs. The amenity premiums were binary at 3% or 27%.

We formulated each of the models for two, three, and four one-year planning periods plus a dummy third (fourth and fifth for the three- and four-period models) period where the budgets were set to zero (54 runs in total plus 9 runs that ignored the feedbacks). In the absence of a zero-budget period at the end of the planning horizon, the parcel selections in the last period would not reflect the presence of land-price feedbacks. The reason for this is that the optimization models are not instructed to look at potential land conversions beyond the end of the planning horizon. Without the dummy period, the objective function value, which is to be maximized by the model, would be based on the state of the parcels at the end of the last period. The price feedbacks would not be constraining in the last period, and as a result, the optimal parcel selection strategies in that period would be similar to those that result from models that ignored the feedbacks completely. We confirmed this argument with extensive preliminary testing. On the other hand, if the objective function is set to maximize biodiversity at the end of the dummy period, then the parcel selections in the period that preceded the dummy period will be optimized, although the price feedbacks and the potential land developments in the dummy period that result from these acquisitions are also taken into consideration.

The first set of questions that we asked was about the optimal attributes of parcels that were selected for conservation in the first period in the models that captured the feedbacks versus the models that ignored them. These aspatial attributes included the average market price, biodiversity value, and conversion risk, along with the total area of the selections and the number of parcels selected. We wanted to know how optimal parcel selection strategies might change in the presence of land-price feedbacks.

Table 1. Optimal Period 1.

		"Smart" purchases (price feedbacks are anticipated)					
		3% amenity			27% amenity		
	Naïve purchases	$\eta^s = 0$	$\eta^s = 0.36$	$\eta^s = 1$	$\eta^s = 0$	$\eta^s = 0.36$	$\eta^s = 1$
		3 planning periods					
US$1 M							
Total							
Area of developments (ha)	200.35	199.40	200.35	200.35	199.93	199.93	199.93
Area of conservation acquisitions (ha)	94.67	56.37	88.16	93.56	62.94	67.41	55.24
Number of acquisitions	12	9	14	11	4	5	8
Average							
Area of acquisitions (ha)	7.89	6.26	6.30	8.51	15.73	13.48	6.90
Market value of acquisitions (US$)	83,323	111,111	71,397	90,389	249,720	199,404	124,985
Irreplaceability of acquisitions	134.29	177.77	148.95	132.45	156.53	145.83	179.25
Conversion risk of acquisitions (US$)	3,936	7,087	4,642	4,204	7,561	5,260	8,156
Objective function value		271,537	271,512	271,500	270,927	270,924	270,911
Optimality gap (%)		0.00	0.00	0.00	0.00	0.00	0.00
US$10 M							
Total							
Area of developments (ha)	200.35	200.35	200.35	200.35	199.93	199.93	199.93
Area of conservation acquisitions (ha)	372.82	209.57	119.63	49.45	124.59	175.85	118.36
Number of acquisitions	39	34	31	21	27	37	32
Average							
Area of acquisitions (ha)	9.56	6.16	3.86	2.35	4.61	4.75	3.70
Market value of acquisitions (US$)	256,403	294,109	322,489	476,137	370,330	270,156	311,931
Irreplaceability of acquisitions	164.00	181.03	191.72	189.15	185.99	176.08	174.06
Conversion risk of acquisitions (US$)	16,557	39,369	52,103	83,454	51,936	37,093	58,253
Objective function value		288,030	287,607	286,895	286,966	286,511	285,778
Optimality gap (%)		0.07	0.05	0.21	0.04	0.23	0.68
US$20 M							
Total							
Area of developments (ha)	199.93	200.35	200.35	200.35	199.93	199.93	199.93
Area of conservation acquisitions (ha)	337.56	219.40	175.25	129.45	210.61	301.68	148.06
Number of acquisitions	55	63	41	38	55	51	46
Average							
Area of acquisitions (ha)	6.14	3.48	4.27	3.41	3.83	5.92	3.22
Market value of acquisitions (US$)	363,635	317,302	487,773	526,014	363,618	392,005	434,742
Irreplaceability of acquisitions	173.75	176.30	187.84	184.03	173.31	161.41	175.93
Conversion risk of acquisitions (US$)	42,668	60,356	73,154	95,724	66,631	50,690	84,511
Objective function value		301,267	300,816	300,221	299,655	298,729	298,487
Optimality gap (%)		0.32	0.32	0.38	0.44	0.78	1.02
		4 planning periods					
US$1 M							
Total							
Area of developments (ha)	200.35	199.93	199.93	199.93	199.93	199.93	199.93
Area of conservation acquisitions (ha)	63.96	58.17	67.35	189.00	68.12	42.90	76.42
Number of acquisitions	7	3	5	5	9	3	9
Average							
Area of acquisitions (ha)	9.14	19.39	13.47	37.80	7.57	14.30	8.49
Market value of acquisitions (US$)	142,829	332,960	199,804	199,768	110,816	331,160	111,108
Irreplaceability of acquisitions	157.62	157.12	121.67	101.74	162.03	185.14	129.05
Conversion risk of acquisitions (US$)	5,318	7,086	5,292	3,961	6,250	9,953	5,924
Objective function value		262,931	262,823	262,791	262,684	261,899	262,491
Optimality gap (%)		0.02	0.09	0.03	0.06	0.38	0.13

Table 1. (Continued.)

		"Smart" purchases (price feedbacks are anticipated)					
		3% amenity			27% amenity		
	Naïve purchases	$\eta^s = 0$	$\eta^s = 0.36$	$\eta^s = 1$	$\eta^s = 0$	$\eta^s = 0.36$	$\eta^s = 1$
US$10 M							
Total							
Area of developments (ha)	200.35	199.17	199.93	199.93	199.93	199.93	199.93
Area of conservation acquisitions (ha)	252.29	175.31	66.01	60.70	139.36	64.13	90.61
Number of acquisitions	41	27	28	31	29	33	25
Average							
Area of acquisitions (ha)	6.15	6.49	2.36	1.96	4.81	1.94	3.62
Market value of acquisitions (US$)	243,857	370,357	356,640	322,315	344,454	303,013	399,586
Irreplaceability of acquisitions	159.22	166.72	183.17	179.42	178.09	173.39	175.18
Conversion risk of acquisitions (US$)	30,300	54,956	71,355	80,888	63,526	77,627	69,027
Objective function value		283,977	286,011	285,795	284,656	284,941	284,664
Optimality gap (%)		1.28	0.59	0.83	0.79	0.68	0.88
US$20 M							
Total							
Area of developments (ha)	200.35	199.93	198.98	199.93	198.98	199.93	199.93
Area of conservation acquisitions (ha)	376.52	113.46	98.06	100.96	153.16	175.37	130.33
Number of acquisitions	71	51	57	51	54	64	50
Average							
Area of acquisitions (ha)	5.30	2.22	1.72	1.98	2.84	2.74	2.61
Market value of acquisitions (US$)	281,170	392,120	350,860	392,125	370,348	312,328	399,888
Irreplaceability of acquisitions	159.57	176.52	175.55	169.88	170.68	176.47	167.42
Conversion risk of acquisitions (US$)	44,873	92,942	92,863	91,398	78,591	67,423	80,635
Objective function value		305,316	304,984	304,528	303,135	301,785	301,982
Optimality gap (%)		0.53	0.63	0.87	0.89	1.37	1.32
			5 planning periods				
US$1 M							
Total							
Area of developments (ha)	200.35	199.93	199.93	199.93	199.93	199.93	199.93
Area of conservation acquisitions (ha)	61.76	59.04	70.66	38.46	29.41	41.36	58.80
Number of acquisitions	7	4	4	4	3	6	4
Average							
Area of acquisitions (ha)	8.82	14.76	17.66	9.62	9.80	6.89	14.70
Market value of acquisitions (US$)	142,766	249,620	249,980	249,033	323,840	166,372	248,968
Irreplaceability of acquisitions	150.39	177.90	128.68	173.10	174.72	170.74	124.09
Conversion risk of acquisitions (US$)	5,676	9,319	5,339	11,090	24,847	13,809	7,434
Objective function value		251,622	252,072	252,032	250,655	251,033	251,144
Optimality gap (%)		0.34	0.19	0.21	0.66–	0.42	0.46
US$10 M							
Total							
Area of developments (ha)	200.35	199.93	199.93	199.93	199.93	199.93	199.93
Area of conservation acquisitions (ha)	185.24	46.39	49.59	51.88	119.53	72.83	59.23
Number of acquisitions	46	12	32	28	21	27	32
Average							
Area of acquisitions (ha)	4.03	3.87	1.55	1.85	5.69	2.70	1.85
Market value of acquisitions (US$)	217,388	776,530	312,448	356,920	475,957	370,369	312,426
Irreplaceability of acquisitions	167.93	188.43	178.91	181.58	186.87	181.45	169.60
Conversion risk of acquisitions (US$)	38,965	94,665	87,101	82,939	68,417	80,019	80,374
Objective function value		282,566	284,312	283,999	283,239	282,867	281,372
Optimality gap (%)		1.55	0.89	1.29	0.94	1.15	1.69
US$20 M							
Total							
Area of developments (ha)	200.35	198.98	199.93	198.98	199.93	198.98	199.931
Area of conservation acquisitions (ha)	347.11	107.81	136.84	141.45	153.03	122.85	126.35
Number of acquisitions	73	56	39	41	37	51	53

Table 1. (Continued.)

		"Smart" purchases (price feedbacks are anticipated)					
		3% amenity			27% amenity		
	Naïve purchases	$\eta^s = 0$	$\eta^s = 0.36$	$\eta^s = 1$	$\eta^s = 0$	$\eta^s = 0.36$	$\eta^s = 1$
Average							
Area of acquisitions (ha)	4.75	1.93	3.51	3.45	4.14	2.41	2.38
Market value of acquisitions (US$)	273,962	357,081	512,700	487,661	539,932	391,498	377,316
Irreplaceability of acquisitions	154.15	173.46	174.40	179.01	174.31	173.57	167.68
Conversion risk of acquisitions (US$)	47,016	89,395	90,950	89,261	83,180	91,204	86,694
Objective function value		308,649	308,274	307,776	306,072	305,568	305,001
Optimality gap (%)		0.70	0.78	1.01	1.53	1.60	1.79

Notes. Parcel selection attributes on Lopez Island, Washington under three annual budget, three supply elasticity, and two amenity premium scenarios and with 3-, 4-, and 5-period planning horizons. The parcel attributes are contrasted to those found by models that ignored the land-price feedbacks (see the columns under the heading "Naïve purchases"). In the vast majority of scenarios, the total area, as well as the total number of parcel acquisitions that are optimal in Period 1, was less than what would be optimal if the feedbacks were not accounted for. Also, in the vast majority of scenarios, the average market and biodiversity values and the average conversion risk of optimal parcel selections in Period 1 were higher than what would be optimal in the absence of the feedbacks. The attributes where these results are invalid are shown with gray backgrounds.

The purpose of the three-, four-, and five-period models was threefold. First, we wanted to know if our proposed model was computationally tractable for longer planning horizons. Second, we wanted to know if the attributes of optimal parcel selections in the first period were any different given different planning horizons. Finally, by comparing the optimal objective values defined at different reference points in time, i.e., at the end of the third, fourth, and fifth periods, we wanted to get a rough estimate of the annual conservation budget that would allow the reversal of ecological decline on the Island brought on by development.

Additional sensitivity analyses were conducted on the biodiversity correction coefficient (α) and on the amenity premium (q) to generate evidence about the robustness, or sensitivity of the potential findings about optimal parcel selections. We created a set of 90 three-period model formulations with α set to 0, 0.1, 0.2, 0.4, 0.6, and 1.0, respectively, at the three annual budget levels (US$1 M, 10 M, and 20 M), at the two amenity premium levels (3% versus 27%), and at the three supply elasticity levels (1, 0.36, and 0). A further nine models were formulated and solved to see how the solutions changed if there were no amenity premiums present in addition to the equilibrium-driven feedbacks.

To assess the conservation costs of ignoring the land-price feedbacks on Lopez Island, the parcel variables of the programs that incorporated the feedbacks were fixed in the first period (the x_{it}s for all $t = 1$) to the values that were obtained by solving the programs with both the amenity premiums and the equilibrium-driven feedbacks set to zero. The "fixed" programs were then resolved, and the resulting period 2 land prices were fed back into the programs with zero amenity premiums and zero equilibrium-driven feedbacks to obtain period 2 parcel selections. These parcel selections were then used to fix the x_{it} variables for $t = 2$, again, in the programs that captured the feedbacks. The process was repeated for the three-period (two periods + one dummy) programs under each scenario to obtain a conservative estimate of the costs. The estimates are conservative relative to what is expected for the four- and five-period models because of the one or two extra periods in the latter models, where the underestimation of land prices due to ignoring the feedbacks can only add to the gap that separates the objective value of the optimal solution from those that ignore the feedbacks. The resulting objective function values for the three-period models, as well as the achieved relative optimality tolerance gaps and the percentage conservation losses, are reported in Table 2 under "Naïve Purchases" in column 4, 5, and 8, respectively. If both the programs that captured the feedbacks ("Smart Purchases") and those that had been "fixed" ("Naïve Purchases") in accordance with the above procedure solved to true optimality, then only one figure was reported for percentage conservation loss. If, on the other hand, the programs that captured the feedbacks did not solve to true optimality within one day of CPU time, the percentage losses were calculated in two ways. First, they were calculated based on the objective function value of the best integer solution that was found (lower bound). Second, to establish upper bounds, they were also calculated based on the objective function value of the best linear programming relaxation that was available at the active nodes in the branch-and-bound tree (Land and Doig 1960) built by CPLEX (IBM-ILOG 2009) to solve the models. The lower and upper bounds on the percentage conservation losses are reported in the last column of Table 2. The values of the true losses were within these bounds.

3.5.1. The Computing Environment. All 162 model instances $(54 + 9 + 90 + 9)$ were formulated using custom MS Visual Basic.NET (2005) code and were solved by multithread, 64-bit IBM-ILOG CPLEX versus 12.1 optimization engines (IBM-ILOG 2009) on either a Power

Table 2. Objective values under different market scenarios and budget constraints.

			Naïve purchases (no anticipation of price feedbacks)		Smart purchases (price feedbacks are anticipated)		
Budget	Price elasticity of supply	Amenity premium (%)	Objective func. values (total biodiversity hectares)	Optimality gaps (%)	Objective func. values (total biodiversity hectares)	Optimality gaps (%)	Loss in objective function values due to ignoring the price feedbacks (%)
US$1 M	1	3	271,525	0.00	271,537	0.00	0.004568
	0.36	3	271,496	0.00	271,512	0.00	0.01
	0	3	271,484	0.00	271,500	0.00	0.01
	1	27	270,168	0.00	270,927	0.00	0.28
	0.36	27	270,002	0.00	270,924	0.00	0.34
	0	27	268,958	0.00	270,911	0.00	0.72
US$10 M	1	3	286,007	0.00	288,030	0.07	0.70–0.78
	0.36	3	286,509	0.00	287,607	0.05	0.38–0.43
	0	3	286,230	0.00	286,895	0.21	0.23–0.44
	1	27	278,586	0.00	286,966	0.04	2.92–2.96
	0.36	27	278,051	0.00	286,511	0.23	2.95–3.19
	0	27	277,908	0.00	285,778	0.68	2.75–3.41
US$20 M	1	3	299,773	0.00	301,267	0.32	0.50–0.81
	0.36	3	299,527	0.00	300,816	0.32	0.43–0.75
	0	3	298,167	0.00	300,221	0.38	0.68–1.06
	1	27	289,092	0.00	299,655	0.44	3.52–3.95
	0.36	27	288,284	0.00	298,729	0.78	3.50–4.24
	0	27	287,452	0.00	298,487	1.02	3.70–4.67

Notes. The columns under “Naïve purchases” show the objective function values and the associated optimality gaps of the modeling solutions that ignored the price feedbacks. The columns under “Smart purchases” show the solutions of the models that captured the feedbacks. Where solutions were not proved optimal (i.e., the optimality gaps were greater than zero), only upper and lower bounds on the objective function losses are given. The lower bounds are the losses relative to the best integer solutions found to the models that captured the feedbacks, whereas the upper bounds correspond to losses relative to the best bounds found.

Edge 2,950 server with four Intel®Xeon®5,160 central processing units (CPUs) at 3.00 Gz frequency and with 16 GB of random access memory, or on a Power Edge 510 with two Intel®Xeon®x5,670 CPUs at 2.93 Gz frequency and with 32 GB memory. The operating system was MS Windows Server 2003 R2, Standard x64 Edition with Service Pack 2 (2003) on the former, and it was MS Windows Server 2008 R2 Standard x64 Edition (2009) on the latter machine. The integer programming instances that incorporated the land-price feedbacks had 76,888 constraints and 34,876 variables (11,160 binary) for the three-period, 122,411 constraints, and 53,011 variables (15,345 binary) for the four-period; and 175,304 constraints and 73,936 variables (19,530 binary) for the five-period models. Those that did not incorporate the feedbacks had much less; 9,769 constraints and 8,370 variables for the 312,560 constraints and 11,160 variables for the four-period, and 15,351 constraints and 13,950 variables for the five-period models. The termination criterion for the optimization runs was a combination of time limit and optimality: the solver was instructed to stop and report the solution after one day (86,400s) of runtime or after proven optimality was achieved, whichever happened first. The achieved optimality gaps are reported in the fifth and seventh columns of Table 1. Entries with 0.00% gaps indicate provably optimal solutions.

Given the purpose of our analyses—to provide strategic suggestions as to how to go about conservation acquisitions in the presence of land-price feedbacks—and the error inherent in the input data sets, we considered solutions within a loose 2% optimality gap to be good feasible solutions. Whenever this target gap was not achieved within one day of run time (some of the US$10 M and US$20 M problems fell into this category), we tried a number of strategies to speed up the optimization process. The one strategy we found very effective was the use of MIP starts from the solutions to the US$1 M problems, and then from the solutions to the US$10 M problems to solve the US$20 M ones. Clearly, the optimal solutions to the US$1 M problems are always feasible for the US$10 M problems, whose solutions are in turn feasible for the US$20 M problems. Because most US$1 M problems solved to optimality in minutes, it was natural to use these as starting points for the problems with bigger budgets.

The solver settings were all default except the integrality tolerance gap, which was set to zero, the working memory limit, which was increased to 1,000 MB from the default of 128 MB, and the node storage switch, which was set to 2 to instruct CPLEX to save node files on disk uncompressed whenever the size of the branch-and-bound tree exceeded the working memory limit. Finally, there were a couple of cases where the solver encountered singular (uninvertable) basis matrices during optimization and terminated without a solution. In these cases, we followed the user's manual (IBM-ILOG 2009) and took the following steps to solve the problem: (1) we increased the limit on the number of times CPLEX was allowed to attempt to repair singular bases from 10 to 100 per singularity, (2) we switched MIP emphasis to 2 to emphasize feasibility over optimality, and (3) we set the scaling parameter to 1 to enforce more aggressive scaling.

4. Results and Discussion

4.1. Computational Results

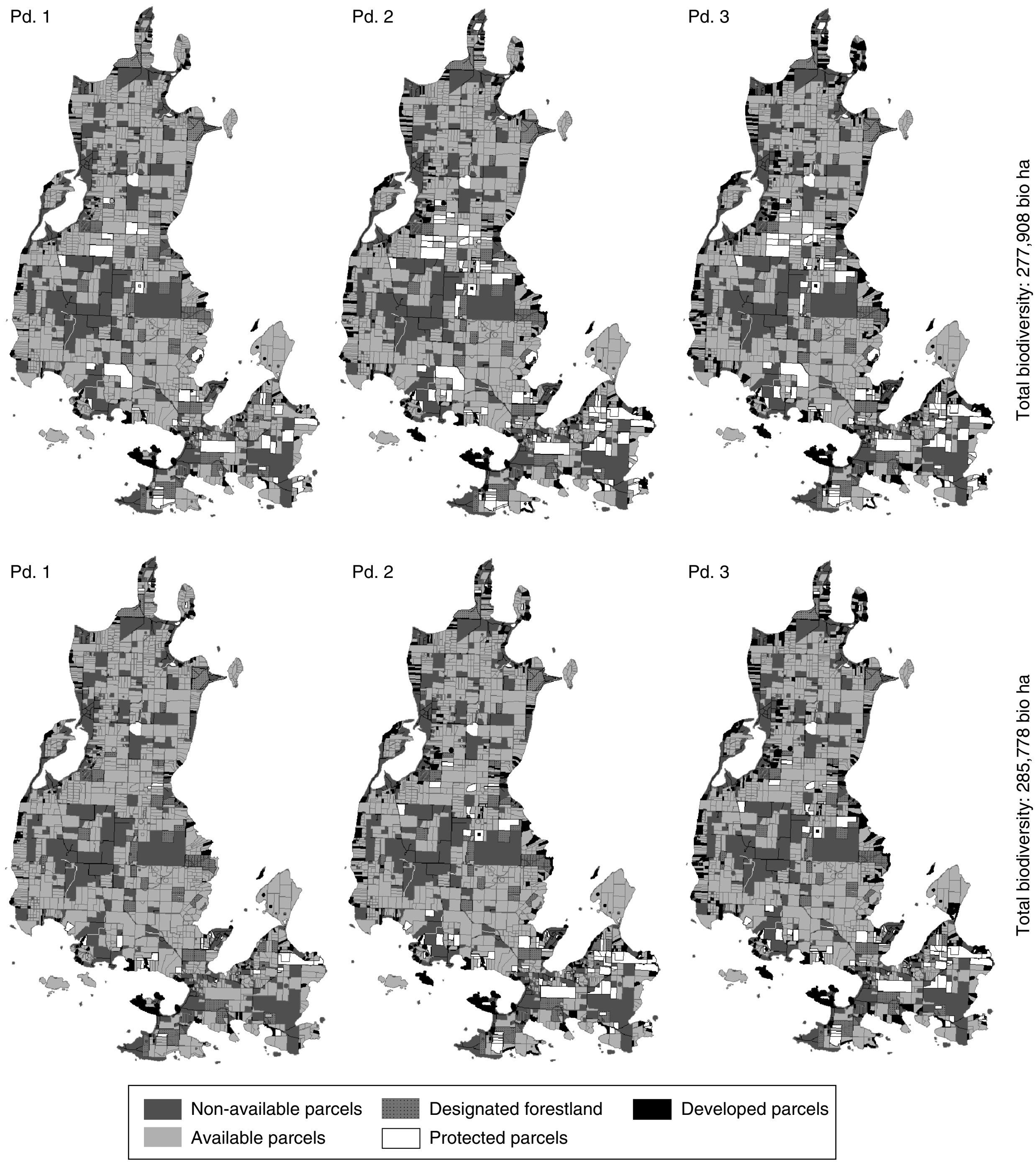
The goal of this section is to demonstrate the computational feasibility of the proposed model as it is applied to a spatially large real problem (see the Sabbadin et al. 2007 classification for what constitutes "large" in the dynamic reserve selection literature) with three-, four-, and five-period long planning horizons using off-the-shelf optimization software (IBM-ILOG 2009) and computational resources in the US\$5,000–\$10,000 price range. All 54 model instances that captured the land-price feedbacks solved to less than 2% optimality gaps within one day of computing time. The six models with the US\$1 million budgets were solved to proven optimality in 14 to 64 minutes for three periods. The four- and five-period models solved to gaps between 0.03 and 0.66% within one day for the US\$1 M budget. The models with US\$10 and \$20 million budgets were much harder: the optimality gaps that were achieved after 24 hours of runtime ranged between 0.07 and 1.79% (Table 1). Although some of the models were hard to solve, none of them were intractable in terms of finding good feasible solutions. Given the complexity and size of the problems, this result is encouraging. It implies that the proposed dynamic reserve selection model can be a computationally viable option for tackling real problems of considerable size. We note that the evaluation of computational feasibility for problems that are larger than the Lopez Island case in terms of the number of sites, or are more complex in terms of the number of planning periods, is likely to be unnecessary. First, land-price feedback effects only arise in markets where conservation competes with development (Armsworth et al. 2006). These markets cannot be large, because scarce conservation dollars can only compete against abundant development dollars if they are channeled to a smaller area that is of particular conservation value. The frequency of these situations in practice and the need for models to address this issue are well documented in the reserve selection literature (e.g., Polasky 2006, Armsworth et al. 2006 or Costello and Polasky 2004). If the analysis area is much larger, conservation is unlikely to be significant enough in the market to induce price feedbacks. In these cases, the proposed model is unnecessary. Second, the need for models with more than five periods is also unlikely because conservation NGOs or local governments are rarely in the position to forecast revenue flows beyond this time frame.

4.2. Solution Analysis

4.2.1. The Conservation Costs of Ignoring the Land-Price Feedbacks. The percentage losses in objective function values due to ignoring the land-price feedbacks varied between 0.0046% for the US\$1 M model at $\eta^s = 1$ and 3% amenity premium and 3.7%–4.67% for the US\$20 M model at $\eta^s = 0$ and 27% amenity premium (Table 2). There is a clear trend that with bigger budgets, the magnitude of conservation losses due to ignoring the feedback effects increases and becomes quite substantial. This is not too surprising, because with bigger budgets more land is in play and more money can be used poorly. The data in Table 2 partly illustrate this point. Higher amenity premiums led to greater relative conservation losses in each budget category. These percentage losses were progressively greater with increased budgets. The more money is in play, the more land can be acquired for conservation but the harder it becomes to avoid the repercussions of high amenity premiums. This is because there is less space left to find good alternatives to sites that provide high conservation values without making the adjacent lots more vulnerable to development, unless, of course, one can minimize these adverse effects using a spatial optimization tool such as the one proposed in this paper. To understand how substantial these losses are, consider the difference in objective function values between the models under the US\$10 M versus the US\$20 M budget scenarios (Table 2). The average percentage loss in objective function values due to moving from a US\$20 M to a US\$10 M annual budget is 4.2% in the model solutions that accounted for the land-price feedbacks. Thus, the negative impact of ignoring the feedbacks under the US\$20 M budget where strong amenity premiums (27%) and perfectly inelastic supply are present is roughly equivalent to the impact of losing US\$10 M or half of the US\$20 M from the annual conservation budget. Whereas these data were derived only from the three-period models, we expect to see similar or more costly trends with four or five periods because of the extra period or two when the underestimation of price feedbacks can only add to the losses in objective values.

4.2.2. Optimal Parcel Attributes in the "Smart" vs. "Naïve Purchases" Models. A closer inspection of the optimal, or near-optimal, parcel selections reveals that the solutions behind the models that ignored the feedbacks versus those behind the models that captured the feedbacks were very different. As an example, Figure 4 shows two sets of maps that illustrate some of the parcel selections (in white) that were found to be optimal (or near-optimal) under the US\$10 million budget scenario. The maps in the top row represent the solution to the model where the land-price feedbacks were ignored, whereas the maps in the bottom show the outcome of the run that captured the feedbacks using zero supply elasticity and a 27% amenity premium. It is clear that the parcel selections in

Figure 4. Optimal parcel selections with a US$10 million annual budget.



Notes. The protected parcels are in white, whereas the developed ones are in black. In the top row, the land-price feedbacks were ignored. In the bottom row, the feedbacks were captured using a perfectly inelastic supply and a 27% amenity premium. Note the stark difference in the amount of protected parcels (white) in the top versus the bottom maps. It is better to buy fewer parcels with less total area, especially in Pd. 1, when the price feedbacks are present.

the first two periods were very different. When the feedbacks were ignored, more parcels and larger areas were selected, especially in Period 1 and in the interior of the island. Numerical data in Table 1 suggest that this observation is not unique to the scenario listed above. In 49 of the 54 models that captured the land-price feedbacks (91%), the total area of optimal conservation acquisitions in Period 1 was lower, sometimes by as much as 87%, (under the US$10 M budget, perfect supply inelasticity and 3% amenity premium scenario) than in the models where the feedbacks were ignored. On average, the total area in Period 1 parcel selections was 41.43% less in the 54 models that captured the feedbacks than in the corresponding 9 models that ignored them (Table 1). The average area of the parcels that were found to be optimal for conservation in Period 1 also decreased in 40 out the 54 models (74%). The number of parcels that were optimal for conservation in Period 1 decreased also, in 51 of the 54 scenarios (94%). On average, the number of parcels dropped by 28.49%. The average market and biodiversity value and conversion risk of the acquisitions in Period 1 on the other hand increased in 49 (91%), 45 (83%), and 51 (94%) of the 54 models, respectively. On average, the market values were 53.14%, the irreplaceabilities were 7.23%, and the conversion risks were 99.6% higher in the model solutions where the feedbacks were accounted for. It is also noteworthy that the above findings do not appear to be sensitive to the length of the planning horizon. On average, the trends are similar even if the three-, four-, and five-period models are considered separately (Table 1).

To check if the above trends were sensitive to different values of the biodiversity correction coefficient (α), we formulated and solved an additional 90 three-period models for $\alpha = 0$, 0.1, 0.2, 0.4, 0.6, and for 1.0. Overall, the trends were similar, although less pronounced than in the $\alpha = 0.8$ models: the total area of optimal Period 1 parcel selections was 12.19% less and the number of parcels was 17.19% less, whereas the market values were 23.03% higher, the irreplaceabilities were 4.83% higher, and the conversion risks were 16.79% higher on average in the models that captured the feedbacks. Nonetheless, there were many scenarios, especially at $\alpha < 0.6$ where the trends were the opposite for some or all of the parcel attributes that we analyzed. Because the appropriate values of α can be narrowed down via expert opinion in practice, we encourage conservation organizations or community planners to use our proposed model and run it for specific values of α before conservation decisions are made.

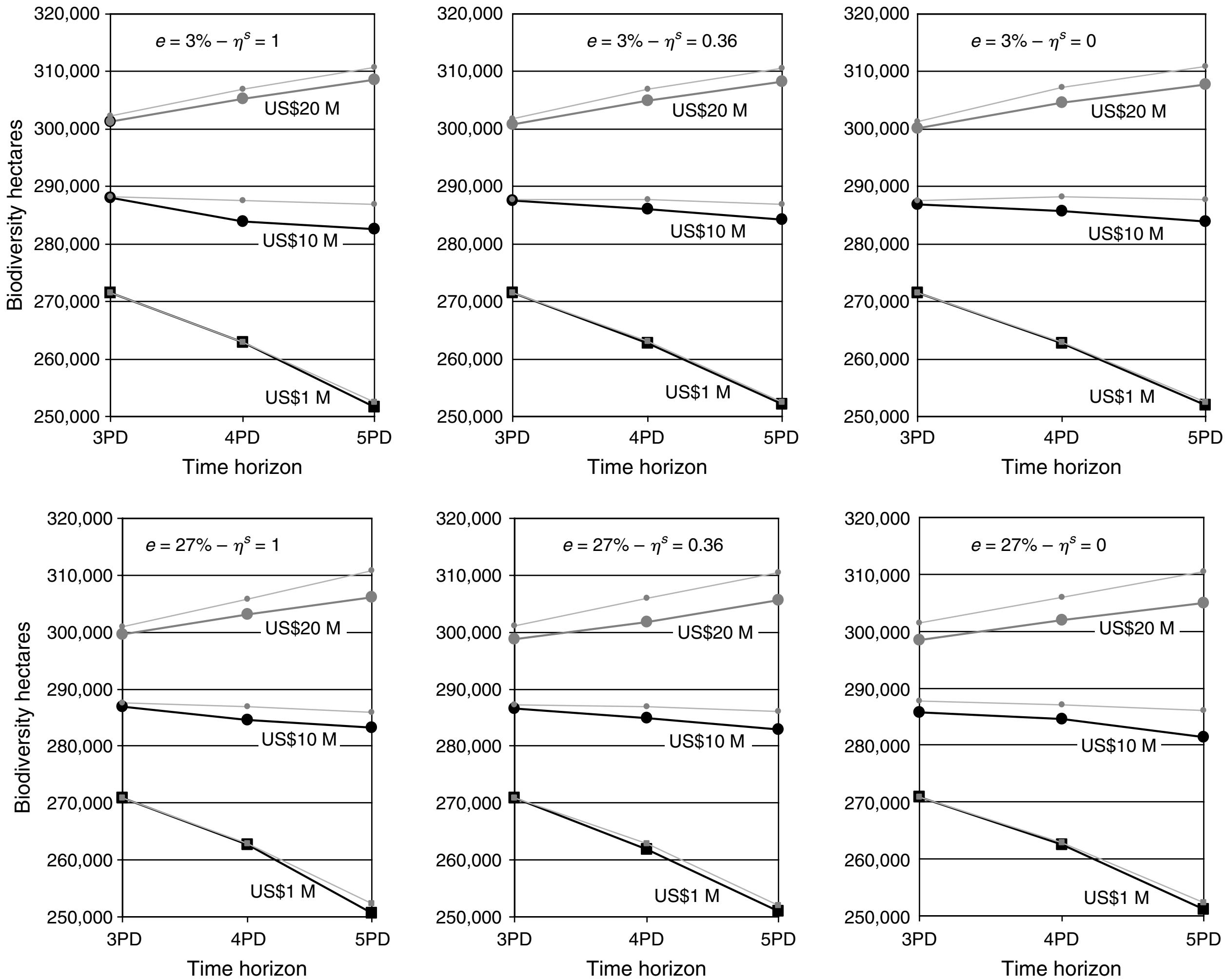
Finally, by setting the amenity premium to 0 and solving nine additional three-period problems with the three alternative budgets and the three supply elasticities, we checked if it made sense to explore the impact of alternative amenity constructs, such as edge-based premiums (e.g., Equation (9′)), on optimal parcel selections in Period 1. In sum, the overall trends did not appear to change much relative to those found for the 3% and 27% premiums: on average it was still optimal to select fewer parcels (21.6% fewer) with less total area (29.8% decrease) but with higher market values (81.1% higher), higher average conversion risks (111.8%), and with higher biodiversity values (5.4%). In a few cases, such as under US$20 M budget and with 0.36 supply elasticity, our recommendation to buy fewer parcels with less total area did not hold for Period 1 if the amenity feedbacks were completely eliminated. We conclude that in most scenarios the type of amenity construct will not affect optimal parcel attributes. Exploring the impact of alternative models (e.g., Equation (9′)) is an option if the elimination of amenity feedbacks leads to results that conflict with what is seen when a particular amenity construct is included in the model. We suspect that the amenity feedbacks have a bigger local impact on the spatial allocation of parcel acquisitions than on aspatial parcel attributes. The exploration of the relative impact of amenity versus equilibrium-driven feedbacks is beyond the scope of this paper.

In the light of the above results and sensitivity analyses, it is clear that the recommendation that sites should be preserved sooner rather than later, and in greater quantity (Snyder et al. 2004), does not necessarily hold in competitive land markets like Lopez Island. Because the magnitude of the land-price feedbacks that are driven by the shifting supply and demand equilibriums depends, partly, on the combined area of conservation acquisitions, it makes sense in many cases not to preserve as much land as would be optimal in the absence of the feedbacks. It is also not surprising that the market and biodiversity values and the conversion risk of the parcels that were found to be optimal for conservation were higher in the models that captured the feedbacks. On a limited area, it makes sense to select high-risk sites that have high conservation values because these conservation values directly contribute to the objective function without necessarily causing unintended losses to development via the price feedbacks.

Finally, it is important to point out that in all of the 54 model scenarios that we analyzed for the effects of land-price feedbacks, it was optimal to spend the available budgets for conservation acquisitions: the budget constraints were always near-binding. The small positive values of the slack variables that were associated with these constraints (between 0.0001 to 0.572% of the available budgets) were consistent with the discrete nature of mixed 0-1 programming. This result is very important because it demonstrates that land acquisitions are strategically effective in biological conservation even in competitive markets where land-price feedbacks are present. There was a concern that the extra development pressure induced by acquisition-driven price increases could lead to net losses in biodiversity. Whether or not the budget constraints remain near-binding if carry-over of funds is allowed is the subject of future research.

4.2.3. The Effect of Conservation Budgets on Biodiversity in the Face of Continuing Development. The objective function values that were derived by the three-, four-, and five-period models under different supply elasticity, and amenity scenarios (Figure 5) refer to the biological conservation status of the Island at the end of the 3rd, 4th, and 5th planning periods, respectively. Comparing these values allows us to make a rough estimate of the minimum annual conservation budget that would be necessary to reverse the declining biodiversity trends on Lopez Island in the face of continuing development pressure. It is clear from Figure 5 that of the three budgets that we considered, it is only with US$20 M where the total biodiversity hectares is in an increasing trend from Periods 3 to 5. This implies that the minimum amount of annual conservation funds that might be necessary to overcome the

Figure 5. Objective function values (in biodiversity hectares) of best integer solutions and best upper bounds found by the 3-, 4-, and 5-period models at the end of their respective planning horizons under US$1 M, $10 M, and $20 M annual budgets with six supply elasticity and amenity premium combinations.



Notes. The lines that connect the objective values of the best integer solutions are thicker and are located underneath those that connect the corresponding objective values for the upper bounds. Note that, of the three budget scenarios, US$20 M is the only one that allows the reversal of continuing declines in total biodiversity hectares on Lopez Island during the next five years.

negative effects of development on Lopez Island is likely to be between US$10 M and $20 M.

5. Conclusion

In this article, we introduced a dynamic reserve selection model that accounted for the two major types of land-price feedback effects that arise in competitive land markets as results of conservation acquisitions. Our proposed modeling approach also captured the unintended development processes that can partly be driven by these mechanisms. The primary methodological contribution is an operational model that can help community planners and conservation organizations identify spatially and temporally explicit site selection strategies in the face of land-price feedback effects. As an illustration of the mechanics of the approach and an example of the policy implications that could be derived, we applied the model to a real market on Lopez Island, United States. We found that the proposed integer programming approach was computationally tractable for a large and complex problem instance.

The specific policy implication of the case study was that community planners and conservation organizations must pay attention to price feedbacks in competitive land markets; otherwise, they risk substantial losses in conservation benefits within a certain area. Contrary to findings from the dynamic reserve selection literature (e.g., Snyder et al. 2004) that suggest that more land should be preserved in the earlier stages of the retention effort, we showed that this strategy might not be optimal in competitive land markets. Because the price feedbacks are driven by the area and the adjacency of the land acquisitions, retaining high-risk, high conservation value parcels whose combined area is smaller than what would be optimal in the absence of the feedbacks will likely produce more biodiversity. Land prices that are endogenous to conservation decisions seem to matter in land retention on Lopez Island. We showed that failure to account for them can lead to biodiversity losses equivalent to the impact of halving a conservation budget of US$20 million.

Lastly, we mention that the spatial attributes of a reserve network, such as connectivity or shape, can be just as critical in the success of many conservation projects as accounting for land-price feedback effects. Although this was not the case on Lopez Island, we like to emphasize that our proposed model structure is compatible with the graph-theoretical constructs and other techniques that have been proposed in the literature to enforce or promote these spatial attributes. As an example, Önal and Briers' (2006) *tail function* can easily be imbedded in our model by representing the parcel set as a directed graph where the parcels are the nodes and their adjacency are modeled as vertices. After introducing a set of variables that represent the flows in the network, formulating the tail function as constraints is straightforward.

Acknowledgments

The authors thank J. F. Raffensperger for the valuable presubmission review and S. Kushch for conceiving Inequality (10″). They also thank the two anonymous referees and the associate editor for the valuable comments. This research was supported by the U.S. Forest Service, Northern Research Station.

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