ECOSEL: Multi-Objective Optimization to Sell Forest Ecosystem Services

By

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Abstract: ECOSEL is a voluntary market that attempts to match willing sellers of forest ecosystem services with willing buyers. Multi-objective mathematical programming is used in conjunction with a public good subscription mechanism to generate and market minimum-cost management alternatives that lead to Pareto-optimal bundles of ecosystem services on a piece of forestland. ECOSEL allows the public to subscribe to the competing alternatives by means of a web-based bidding platform. The management alternative that attracts the highest total of bids over the associated opportunity cost (a.k.a., threshold cost or reserve price) wins the auction. The landowner is legally bound to implement the winning plan in return for the profit that arises between the proceeds and the costs of the plan. We discuss how the mechanism can ensure additionality and minimize free riding and highlight some of the empirical results that we obtained via experimental auctions to optimize mechanism design. The goal of this paper is to show how multi-objective programming can be used to generate minimum-cost management alternatives for a real auction where optimal production plans for carbon sequestration, mature forest habitat and timber revenues are to be identified. The case study is suggestive of one of the most sophisticated uses of ECOSEL that might work for some but not all forest landowners. Examples of less involved uses are also given to illustrate low transaction cost applications both within and beyond forestry.

Keywords: ecosystem services, contribution games, multi-objective mathematical programming

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Introduction

ECOSEL is a voluntary market mechanism that attempts to match willing sellers of forest ecosystem services with willing buyers. Potential sellers are landowners who want to generate extra revenues from their land. Potential buyers are private individuals, companies, and philanthropic organizations who are willing to pay to have a say in how the landowner's land is managed over a specific period of time. ECOSEL is an auction platform that allows both competitive and collaborative bidding on alternative management plans that are offered by the landowner. Whichever plan attracts the highest total of bids over the associated cost of the plan (a.k.a., reserve price or threshold cost Fig. 1) is implemented by the landowner who is legally bound to the contract. Multi-objective optimization is used to identify minimum cost plans that lead to different bundles of ecosystem services. In this paper, we provide a brief introduction to the ECOSEL concept, discuss how the mechanism can complement existing instruments that try to increase the provision of ecosystem services, and use a case study to illustrate the process of developing a real auction.

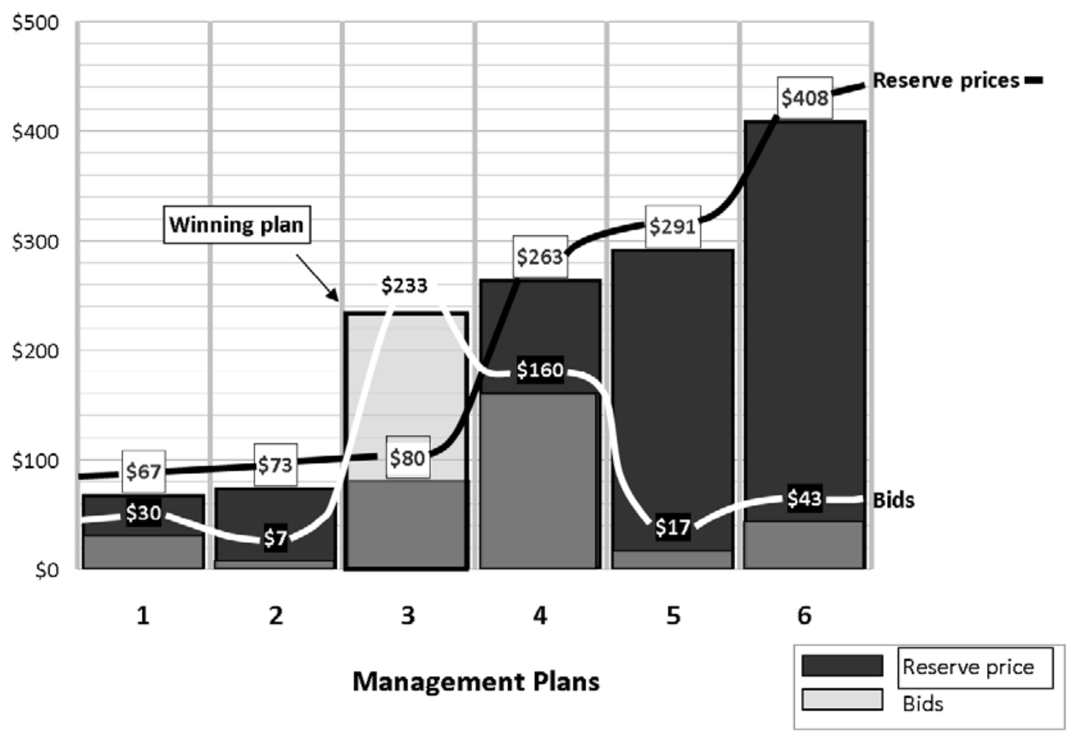


Fig. 1: The ECOSEL bidding platform. The dark grey bars represent reserve prices, while the light, transparent grey ones represent bid totals. Plan 3 is the only management plan in this hypothetical case where the total of bids exceeds the reserve price.

Forests provide a multitude of services. Some of these services are private goods, such as wood or bioenergy and some are public such as viewshed services or habitat for wildlife. Public goods are hard to sell for monetary gains on conventional markets because those who don't pay cannot be excluded from enjoying the benefits (non-excludability), and because the consumption of these goods does not affect their supply (non-rivalry, Pagiola et al. 2002). The fact that one enjoys a forest scenery does not compromise the ability of others to derive similar benefits. The lack of markets for forest ecosystem services has severe ecological and economic consequences. Landowners, trying to maximize financial returns might sell their land for development, thereby contributing to urban sprawl (Alig et al. 2003) and other problems, or they might resort to exploitative timber practices that can also compromise ecosystem functions. Once the environmental damages associated with these activities became apparent, society responded by regulating what forest landowners can and cannot do (e.g., Endangered Species Act: United States Congress 1973). New tax programs and subsidies were created to incentivize good- and penalize bad "behavior". Apart from the obvious costs of regulation and questions of fairness, command-and-control policies often backfire and lead to unintended consequences. Landowners in the Northwest United States who sell their land in riparian areas for development are better off than those who don't because they face fewer restrictions (Bradley et al. 2009). Those who create wildlife habitat via responsible forest stewardship are subject to strict regulations as soon as their work bears fruits and an endangered species gets established. Forest regulation in industrial nations has also been implicated in increasing timber imports from sources that lack the checks and balances required for sustainable stewardship (*leakage*). While fixes often exist to address these problems (e.g., safe harbor agreements for creating wildlife habitat), they are not without costs such as legal fees and lengthy processing times.

Other regulatory mechanisms that can be used to increase the provision of forest ecosystem services include cap-and-trade programs. These schemes rely on threshold amounts of benefits, such as ecosystem services, or of damages, such as carbon emissions, set by central planners. Excess emissions and under-provisions are offset by the polluter (or the under-provider) who purchases credits from those who comply with the caps. While afforestation and other forest projects can lead to carbon sequestration, there is ongoing debate about exactly what activities should qualify for offsetting emissions. A much bigger issue with cap-and-trade programs is related to setting the caps to ensure both a healthy trade and *additionality*. Estimating baseline behavior in the absence of rewards or penalties is typically guesswork. As a result, setting the caps so that they are not overly restrictive to allow trade, and that they are not too lax to encourage changes in behavior, is challenging. The historical price volatility of carbon credits at the European Emissions Trading Scheme and the lack of meaningful constraints in emissions allowances is an example of this problem. A second reason of volatility stems from the fact that cap-and-trade schemes create asset markets that are prone to speculation and boom-and-bust cycles very much like housing markets.

Lastly, we mention forest certification as the most common example of voluntary mechanisms that aim to protect forest ecosystems. Providers of certification programs, such as the Forest Stewardship Council, ensure sustainable forestry by periodic audits. Participants of the program bear the costs of certification in the hope of better market access to consumers who prefer wood products that come from demonstrably sustainable sources. Unlike ECOSEL, forest certification cannot guarantee minimum cost provisions. The case study that follows provides an example of this problem. Cost efficiency is critical if landowners are to buy in a program on a large scale and is a necessary condition for economically efficient management of natural resources.

ECOSEL ensures minimum cost management alternatives that lead to desired bundles of ecosystem services via the use of multi-objective optimization. The mechanism can guarantee additionality if transactions occur by offering participants the opportunity to bid on commodity production options such as timber or development rights. In this scenario, the ECOSEL market will make the baseline scenario explicit based on how developers, sawmills or logging companies bid for commodity options. The market will ensure that no services are under- or overpaid, thereby allowing environmental groups to target their dollars where they can have the largest impact. ECOSEL allows these groups to divert funds from hefty legal fees and use them more directly to promote ecosystem services and compensate landowners for the associated opportunity costs. Lastly, the bidding process can lead to substantial time savings over legal processes or professional lobbying.

While ECOSEL does not rely on expensive central planning to make critical decisions (e.g., setting caps), third-party monitoring is often required to ensure landowner compliance. This adds to the transaction costs via higher reserve prices. The monitoring process is more involved when differences between alternative management plans are subtle. As an example, differences in thinning intensities, fuel treatments or species composition are likely to require an expensive effort. On the plus side, monitoring is rather straightforward and inexpensive when public goods of the *binary type* are sold, such as forest road decommissioning services or foregone clear-cuts. In these cases, the buyers have the option to monitor compliance themselves (e.g., via aerial or satellite images) to minimize costs.

In a game theoretic context, ECOSEL is a competitive multi-unit public goods subscription mechanism of incomplete information and asymmetric preferences (Tóth et al. 2010). ECOSEL games resemble auctions in that the bids can compete to reflect asymmetric preferences and that seller revenue is one of the objectives. ECOSEL is also a subscription game: bids placed on the same plan add up giving rise to cooperation. The notion of "incomplete information" refers to the fact that bidders might not know the preferences of other players prior to the auction. Lastly, ECOSEL is a multi-unit game where multiple, mutually exclusive options (e.g., management plans) are offered for bidding.

To date, ECOSEL research has focused on mechanism design. Deriving Nash equilibria analytically for the ECOSEL game is beyond reach (Rabotyagov et al. In Review) as even two-player subscription games of similar structure are largely intractable (Alboth et al. 2001, Barbieri and Malueg 2008a, 2010, Laussel and Palfrey, 2003, Menezes et al. 2001). This leaves empirical testing and simulation as viable options to optimize design. Rabotyagov et al. (In Review) have shown that offering fewer bundles of services in the auction is more likely to lead to seller profit. The authors also found that allowing communication among the bidders was conducive to outcomes that yield greater social surplus. Since research in other subscription games suggests that social norms (Levy-Garboua et al. 2009), moral motivation (Brekke et al. 2002) and "warm-glow" effects (Andreoni 1990) can have a positive effect on contributions, ECOSEL leaves the communication and confidentiality settings to the players. Another important result of Rabotyagov et al. (In Review) concerns threshold cost disclosure: whether or not threshold costs should be disclosed to the bidders or if the bidders should only be notified when the value of contributions exceeds the reserve price for a particular bundle. In the latter scenario, the bidders might need to cooperate to bracket the threshold costs via repeat bids. Such a coordination problem might pose a hurdle to efficiency but it could increase seller profit. Rabotyagov et al. (In Review) found that there was a range of public good values where the non-disclosure policy dominated the disclosure policy both in terms of seller profit and social surplus. There is a tradeoff, however, between these two criteria when the expected value of the services that are offered is outside that range. In lower-value auctions, disclosing threshold costs is preferable on efficiency grounds but leads to lower seller profit. In high-value auctions, the disclosure policy is preferable for seller profit but non-disclosure if preferable on efficiency grounds. Seller profit is important to increase landowner buy-in for the mechanism.

While Tóth et al. (2010) provided a game theoretical characterization of the ECOSEL concept, Rabotyagov et al. (In Review) focused on empirical mechanism design. In this paper, we show via a case study how multi-objective mathematical programming can be used in ECOSEL games to identify minimum-cost management alternatives for bidding. Using the University of Washington's 1,700 ha Pack Forest (Eatonville, Washington, United States) as an example, we derive a set of spatially-explicit harvest plans that are Pareto-optimal with respect to maximizing timber revenues, carbon sequestration and contiguous mature forest habitat. We contrast the costs of the plans to those derived based on FSC certification criteria. Our goal is to illustrate the process of developing an actual ECOSEL auction and highlight the benefits of optimization in finding low-cost bundles of ecosystem services (*ecofolios*). In this paper, the term ecofolio refers to both the management plan and the bundle of ecosystem services that is projected to result from the plan.

Multi-objective Optimization in ECOSEL

One important although nonessential feature of ECOSEL is its capability to identify minimum-cost management plans for bidding that lead to various bundles of ecosystem services. Cost minimization allows the reserve prices of the plans to be kept low, which in turn is more likely to attract bidders. Minimum cost planning is also likely to afford credibility for the mechanism since it ensures that investors maximize their conservation returns by putting their money only where it is truly needed as a function of all players' bids.

Identifying Pareto-optimal ecofolios requires that the desired services, as well as the costs, are defined as objective functions that are either to be maximized or minimized, and that the existing rules and regulations that are applicable to the property are defined as constraints, expressed in terms of inequalities. Both the objectives and the inequalities are functions of the management actions (e.g., clear-cut a stand or not) that have an impact on ecosystem services and are subjected to bidding during the auction. The general structure of the multi-objective program is:

$$\mathrm{P} = \underset{x}{Max}\{\, f_1(x),\, f_2(x), \ldots f_n(x) : g(x) \le 0, x \in \{0,1\}\} \qquad (1)$$

In Eq. (1), x is a vector of binary choice variables (e.g., harvest decisions for forest stands), and $f_i(x)\ \forall i \in \{1, 2, \ldots n\}$ is a set of objectives that defines the ecosystem services, commodity outputs and opportunity costs as functions of the choice variables. The vector of inequalities, $g(x) \le 0$, denotes the set of applicable constraints that impose logical, operational and technological restrictions on the decision variables. The management decisions are best modeled as discrete choice variables: $x \in \{0,1\}$. Economic theory suggests that public good provision mechanisms, such as ECOSEL, are more likely to lead to efficient outcomes if the goods to be provided are of the discrete type (Barbieri and Malueg 2008a, b). Discrete services, e.g., whether to cut a forest stand in a particular point in time or not, are more straightforward and less expensive to monitor by third parties or by the buyers themselves.

In the next section, we discuss how Program P can be formulated for an actual organization wanting to run a real ECOSEL auction.

Case study: Pack Forest, Washington (US)

The University of Washington's 1,700 ha, 186-stand Pack Forest is managed by the Center for Sustainable Forestry with a mission to demonstrate responsible forest stewardship and to provide funds for student and community programs. Program funds are generated by timber sales, however, the relative proximity of the Forest to the Seattle-Tacoma Metropolitan Area has increased the pressure for real estate development. As a preemptive step, the Pack Forest Administration decided to use ECOSEL to monetize the Forest's ecosystem services in the hope that the proceeds would be sufficient to close at least some of the gap between timber and real estate revenues. Greater gaps suggest higher risks of conversion (Bradley et al. 2009).

(1) Basic Model

Preliminary stated preference surveys and focus group analyses suggest that carbon sequestration and the protection of wildlife habitat associated with old-forest patches are the primary services of interest among stakeholders and the general public. Based on this information, we formulate three functions, each of which is to be maximized and is driven by harvest decisions:

$$\max\left(\sum_{i,p} r_{ip}x_{ip}, \sum_{i,p} co_{ip}x_{ip}, \sum_{i,p} a_i z_{ip}\right) \tag{2}$$

where $i \in N$ counts stands and $p \in P$ counts planning periods ($|P| = 6$ 5-yr periods or 30 years), and where:

x_{ip} = a binary prescription variable that takes the value of 1 if stand i is to be harvested in period p, 0 otherwise; if $x_{i0} = 1$, stand i is not to be cut during the planning horizon;

z_{ip} = a binary indicator variable that takes the value 1 if stand i is part of at least one contiguous cluster of stands in period p whose combined area exceeds the minimum contiguous patch size and where each of the stands meets a minimum age requirement for maturity;

r_{ip} = the discounted timber revenues associated with harvesting stand i in period p;

co_{ip} = the total carbon in 1,000 Mg C that accumulates in (and under) stand i by the end of the planning horizon if it is harvested in period p; and

a_i = the area of stand i.

The first function in (2) maximizes the total discounted timber revenues that can be realized by cutting some subset of the 186 stands in Pack Forest over a 30-yr long planning horizon. Since the length of the planning horizon is less than the minimum rotation age (45 years) used in the Forest, the stands can be cut at most once. We also assume that if there is a harvest, it is done in the midpoint of one of the six 5-yr planning periods. Plating sites assures that regeneration takes place within 5 years of harvests. The revenue coefficients were calculated as a sum of projected forest product volumes times the associated prices that were assumed to remain constant in real terms. Data from about 400 forest plots with continuous inventory between 1995 and 2010 were used in conjunction with the Forest Vegetation Simulator (FVS) to project stand growth in terms of forest product volumes over the 30-year horizon given various harvest timings. The role of the revenue function is to gauge the minimum opportunity costs to the landowner to achieve various combinations of ecosystem outputs from the other two objective functions in (2). Since timber revenues, carbon sequestration and old-forest habitat production are competing services, there will be multiple solutions (harvest schedules) to the optimization model leading to various outputs with respect to each of these functions. One of these solutions, the profit maximizing harvest plan will serve as a benchmark to calculate the opportunity costs for the rest of the solutions. These opportunity costs will be the basis of the reserve prices in the subsequent auction.

The second function in (2) maximizes total carbon sequestration that is projected to occur in the 186 stands over the 30-year long planning horizon at Pack Forest. The total carbon is the sum of projected net increases and decreases in aboveground, belowground and decaying carbon pools in response to the various harvest schedules. Initial stand carbon was calculated from permanent plot data using individual stem diameters and heights and species-specific allometric volume equations to calculate total above- and belowground C for the dominant species (after Shaw 1979, Standish et al. 1987), using stand-level FVS outputs. Equations from Jenkins et al. (2003) were used for the less studied species. To keep track of the carbon in trees that died during simulation and to account for decay, we used a probability function, based on Reinhardt and Crookston's (2003) FVS Fire and Fuels Extension Model that transferred snags to a coarse woody debris C pool. The carbon in this pool was added to the carbon in the standing live biomass to arrive at the co_{ip} coefficients that were used in the model.

Lastly, the third function in (2) maximizes the total area of old-forest habitat over the planning horizon that occurs in contiguous patches of a predefined minimum size and age. The age threshold for old-forest habitat was set to 100 years, while the minimum patch size was set at 100 ac ($A_{\min}$). These settings were designed to enforce a forest landscape that would provide as much mature forest habitat as possible in large contiguous patches given varying amounts of forgone timber revenues. The spatial contiguity and maturity of the patches were controlled via constraints (3)-(9) using the constructs of Rebain and McDill (2003a, b). This formulation requires that a complete set (set Ω) of clusters of stands whose combined area just exceeds the minimum patch size is enumerated pre-optimization. Letting M denote one such cluster in Ω (i.e., $\sum_{i\in M} a_i \geq A_{\min}$ but $\sum_{i\in M\setminus\{j\}} a_i < A_{\min}$ for some $j \in M$), we have the following constraint structure to define the behavior of variable z_{ip} :

$$\sum_{j \in J_{ip}} x_{ij} \geq o_{ip} \qquad \forall i \in N, \;\; p = j_M, \ldots, |P| \tag{3}$$

$$\sum_{j \in J_{ip}} x_{ij} \leq |J_{ip}| o_{ip} \qquad \forall i \in N, \;\; p = j_M, \ldots, |P| \tag{4}$$

$$\sum_{i \in M} o_{ij} \geq |M| b_{Mp} \qquad \forall M \in \Omega, \;\; p = j_M, \ldots, |P| \tag{5}$$

$$\sum_{i \in M} o_{ij} - b_{Mp} \leq |M| - 1 \qquad \forall M \in \Omega, \;\; p = j_M, \ldots, |P| \tag{6}$$

$$\sum_{M \in \Omega : i \in M} b_{Mp} \geq z_{ip} \qquad \forall i \in N, \;\; p = j_i, \ldots, |P| \tag{7}$$

$$\sum_{M \in \Omega : i \in M} b_{Mp} \leq |M \in \Omega : i \in M| z_{ip} \qquad \forall i \in N, \;\; p = j_i, \ldots, |P| \tag{8}$$

$$\sum_{i \in N_{jp}} a_{ip} z_{ip} \geq K_p \qquad p = j_k, \ldots, |P| \tag{9}$$

where:

o_{ip} = a binary indicator variable that is equal to 1 if stand i is older than the minimum maturity age (100 years) in period p;

b_{Mp} = a binary indicator variable that is equal to 1 if every stand in M is older than the minimum maturity age (100 years) in period p;

M = a set of stands that form a contiguous cluster with a combined area that just exceeds the minimum patch size (100 ac);

J_{ip} = the set of all prescriptions under which stand i can mature by period p;

j_i = the first period in which stand i meets the age requirement for maturity;

j_M = the first period in which every stand in cluster M meets the age requirement for maturity;

N_{jp} = the set of stands that can mature by period p;

K_p = the minimum area of mature forest habitat in period p (100 ac); and

j_k = the first period in which the minimum area of mature forest habitat (K_p) must be met (6).

Constraints (3)-(4), (5)-(6), and (7)-(8), each work in pairs. Constraints (3)-(4) force indicator variable o_{ip} to take the value of 1 if and only if stand *i* is older than the minimum age of maturity (100 years) in period *p*. Constraints (5)-(6) drive the b_{Mp} s and allow them to turn on (be equal to 1) if and only if every single stand in cluster *M* is older than the minimum age of maturity in period *p*. Lastly, Constraints (7)-(8) feed the third objective function in (2) with the values of mature patch indicators: z_{ip}. They allow these variables to turn on if and only if at least one cluster that contains stand *i* is on. Constraint set (9) requires that at least one patch of mature forest habitat (100 ac) must be present in the forest by period 6 (the last period).

To ensure that the State of Washington's maximum harvest opening size restriction of 120 ac is never exceeded, we require that

$$\sum_{i \in C} x_{ip} \leq |C| - 1 \qquad \forall C \in \Lambda^{+}, \quad p = j_C, \dots, |P| \tag{10}$$

where $C \in \Lambda^{+}$ are contiguous sets of stands with a combined area that just exceeds $A_{\max}$ (120 ac), and j_C is the first period in which all stands in C are mature enough (i.e., older than the 45 year minimum rotation age) to be cut. These inequalities are called Path Constraints after McDill et al. (2002) who first proposed their use in harvest scheduling. The formulation of Path constraints requires that set Λ^{+} is enumerated pre-optimization. We used Goycoolea et al.'s (200(0 Algorithm I for this purpose.

The rest of the constraints capture various notions of sustainability as defined by the Pack Forest Administration:

$$\sum_{i,p} cc_{ip} x_{ip} \geq C_s \tag{11}$$

$$\sum_{p} x_{ip} = 1 \qquad \forall i \in N \setminus \{N_r \cup N_f \cup N_t\} \tag{12}$$

$$x_{i0} = 1 \qquad \forall i \in \{N_r \cup N_f \cup N_t\} \tag{13}$$

$$\sum_{i} v_{i,p+1} x_{i,p+1} \leq u \sum_{i} v_{ip} x_{ip} \qquad \forall p \in P \setminus |P| \tag{14}$$

$$\sum_{i} v_{i,p+1} x_{i,p+1} \geq l \sum_{i} v_{ip} x_{ip} \qquad \forall p \in P \setminus |P| \tag{15}$$

$$\sum_{i\in N\setminus\{N_r\cup N_f\cup N_t\},p}\left(t_{ip}-\overline{ET}\right)a_i x_{ip}\geq 0 \tag{16}$$

where:

cc_{ip} = the net change in the amount of aboveground carbon in stand i if it is cut in period p;

C_s = the current amount of simple carbon in the entire forest ($237,631.96$ Mg C);

N_r = a set of 25 stands (of the 186) that are reserved with no harvests allowed;

N_t = a set of 10 stands that can only be thinned;

N_f = a set of 8 stands that are set aside for forestry research;

v_{ip} = the total projected timber volume in stand i in period p;

u,l = upper and lower bounds on harvested volume fluctuations from one planning period to the next ($u=1.2$, $l=0.9$);

t_{ip} = the projected age of stand i at the end of the planning horizon if it is cut in period p (t_{ip} is equal to the initial age of stand *i* plus the length of the planning horizon if $p=0$); and

$\overline{ET}$ = the minimum average ending age of the forest, ($\overline{ET}=10$ periods or 50 years).

Constraint (11) requires that the total amount of projected aboveground carbon in the forest must be at least as much as it was at the beginning of the planning horizon. Constraint set (12) specifies that stands that are neither reserves, nor research or thinning-only set-asides can be cut at most once during the 30-year planning horizon. Constraint set (13) fixes the no-action harvest prescription variables that are associated with reserves and research and thinning-only set-asides to 1. This requirement, along with constraints (12), ensures that stands in sets N_r, N_f, and N_t are never cut during the planning horizon. This, self-imposed restriction can be viewed as seed capital to the auction and it represents the amount of services that Pack Forest is willing to contribute beyond what is required by regulations for free of charge. Constraints (14)-(15) set the allowable increase (20%) and decrease (10%) in harvest volumes between adjacent planning periods. The goal of these constraints is to ensure a relatively smooth flux of timber production over the planning horizon. The last of the sustainability constraints, Constraint (16), requires that the area-weighted average age of the stands at Pack Forest that are not reserves or research and thinning-only set-asides exceeds a predefined threshold (50 years) at the end of the planning horizon. This constraint prevents “early cherry-picking”. In other words, it discourages harvesting the most valuable stands early in the planning horizon and leaving the poor sites for later periods. Since the average initial age of the forest is only 45 years, this constraint can also be viewed as seed capital provided by Pack Forest.

Finally, Constraints (17)-(20) specify the decision and indicator variables as binary.

$$x_{ip} \in \{0,1\} \qquad \forall i, p \tag{17}$$

$$o_{ip} \in \{0,1\} \qquad \forall M \in \Omega, \quad p = j_m, \ldots, |P| \tag{18}$$

$$b_{Mp} \in \{0,1\} \qquad \forall M \in \Omega, \quad p = j_m, \ldots, |P| \tag{19}$$

$$z_{ip} \in \{0,1\} \qquad \forall i, p. \tag{20}$$

The three-objective mixed integer program (1)-(20) is called the Basic Model; it represents a forest management scenario at Pack Forest that follows Washington State Forest Practices and conforms to the Sustainable Forestry Initiative’s certification criteria. In an attempt to create ecofolios that might be more attractive to some bidders, we also formulated two additional models. The first one, called the FSC Certification model, incorporates constraints and coefficients that ensure compliance with FSC certification standards. We created three variants of this model, FSC-65, 85 and 105, based on three different assumptions about the age at which the mean annual increment (cMAI) culminates in the stands at Pack Forest. The Pacific Coast Standard of FSC requires that 30% of the pre-harvest basal area is retained in stands where the cMAI has not been reached. Above the age of cMAI, only 10% retention is required. The second model, called the Thinning Model, allows only thinning prescriptions. We formulated two variants, one for 10 and one for 20-year thinning intervals. The idea was to create management alternatives for the auction that would retain contiguous cover across Pack Forest.

(2) FSC Certification Models (FSC-65, 85, 105)

Apart from the basal area retention rules outlined above, the FSC’s Pacific Coast Standard has stricter harvest opening size and green-up requirements than Washington State or the Sustainable Forestry Initiative. In addition to a maximum harvest opening size restriction of 60 ac, which is half of what is allowed by the State, the FSC also specifies a maximum average harvest opening size, which is 40 ac. Finally, instead of the 5-year green-up that is dictated by the State, Pack Forest would have to use a 10-year harvest exclusion period to comply with FSC. The FSC standard requires that harvests on adjacent management units with a combined area above 60 ac can only take place if sufficient time (a.k.a., green-up period) elapses between the harvests to allow regeneration to reach either an average height of 10 ft or full “canopy closure along at least 50% of it s perimeter” (FSC, 2010). Based on management experience, we assumed that 10 years was necessary for these conditions to develop after harvest at Pack Forest.

To enforce the 10-year green-up, we replaced Constraint Set (10) with (21):

$$\sum_{t=p}^{t+g-1} \sum_{i \in C} x_{it} \leq |C| - 1 \qquad \forall C \in \Lambda^{+}, \quad p = j_C, \ldots, |P| \tag{21}$$

where g denotes the length of green-up in periods, and t is a counter for planning periods. All other notation is the same as before.

To impose the maximum average clear-cut size of 40 ac in addition to the maximum clear-cut size limit of 60 ac, which is captured in Constraints (21), we employed Goycoolea et al.’s (2005) Cluster Packing Method that requires the enumeration of yet another set of clusters of stands: Λ^{-}. Unlike set Λ^{+} in constraints (10) and (21) that comprises contiguous clusters of stands whose combined area just exceeds $A_{\max}$, set Λ^{-} consists of clusters with total areas less than or equal to $A_{\max}$. Let $G \in \Lambda^{-}$ denote one such cluster, representing feasible sets of stands that can be harvested simultaneously. In Cluster Packing, each of the feasible clusters is associated with a binary variable that represents whether or not the cluster should be cut in a particular planning period. In our implementation of the FSC Model, we retained the stand-based harvest prescription variables (the x_{ip} ’s) from the Basic Model and mapped them using Constraints (22) and (23) to the new cluster variables (f_{Gp}):

$$\sum_{i \in G} x_{ip} \geq |G| \, f_{Gp} \qquad \forall G \in \Lambda^{-}, \quad p = j_G, \ldots, |P| \tag{22}$$

$$\sum_{i \in G} x_{ip} - \sum_{i \in A_G} x_{ip} - f_{Gp} \leq |G| - 1 \qquad \forall G \in \Lambda^{-}, \quad p = j_G, \ldots, |P| \tag{23}$$

$$f_{Gp} \in \{0,1\} \qquad \forall G \in \Lambda^{-}, \quad p = j_G, ..., |P| \tag{24}$$

where f_{Gp} is a binary variable that equals 1 if all stands in Cluster G are scheduled for harvest in period p, j_G is the first period in which all stands in G are mature enough to be cut, and A_G is the set of stands that are adjacent to Cluster G.

Constraints (22)-(23) force indicator variable f_{Gp} to take the value of 1 if all stands in Cluster G but none adjacent to it are scheduled to be cut in period *p*. Constraint Set (24) defines the cluster variables as binary. To avoid double-counting harvested areas, it is also necessary to require that any one stand can only be part of one, and only one cluster:

$$\sum_{G \in \Lambda^{-}: i \in G} f_{Gp} = 1 \qquad \forall i \in N, \quad p = 1, 2, ..., |P|. \tag{25}$$

Finally, to impose the maximum average harvest opening size limit ($\bar{a}$), we add the following constraint based on Murray et al. (2004):

$$\sum_{p \in P, G \in \Lambda^{-}, i \in G} a_i f_{Gp} \leq \bar{a} \sum_{p \in P, G \in \Lambda^{-}} f_{Gp} \tag{26}$$

In sum, the FSC Certification Model is the same as the Basic Model (1)-(20) except that Constraints (22)-(26) are added to the model, Constraint (10) is replaced with Constraint (21), and the volume, carbon and revenue coefficients are replaced based on the projections that were subject to the FSC rules re basal area retention.

(3) Thinning Models

The thinning models were developed to provide the bidders with very low-intensity management alternatives that exclude clear-cutting as a management tool. The two thinning models, Thin-10 and Thin-20, differed based on the frequencies of thinning entries. In the absence of clear-cuts, neither the maximum nor the maximum average harvest opening size restrictions were applicable in these models. Green-up and basal area retention rules did not apply either for the same reasons. One final consequence of the thinning-only assumption is that these scenarios lead to the same amount of mature forest habitat by the end of the planning horizon as the do-nothing scenarios (164.87 ha). We assumed that thins were done to increase rather than decrease the average age of the stands and therefore thinned stands were eligible for being parts of mature forest patches. As a result of mature forest habitat services being constant, the thinning models were optimized only across the two objectives of net timber revenue maximization (27) and carbon sequestration (28):

$$\max \sum_{i,p}\left(r_{ip}t_{ip} + \sum_{q} r_{ipq}t_{ipq} \right) \tag{27}$$

$$\max \sum_{i,p} co_{ip}t_{ip} \tag{28}$$

s/t:

$$\sum_{p} t_{ip} = 1 \qquad \forall i \in N \setminus \{N_r \cup N_f\} \tag{29}$$

$$t_{i0} = 1 \qquad \forall i \in \{N_r \cup N_f\} \tag{30}$$

$$t_{ip} = t_{ipq} \qquad \forall i, p, q \tag{31}$$

$$\sum_{i,p} cc_{ip}t_{ip} \geq C_s \tag{32}$$

$$\sum_{i} v_{i,p+1}t_{i,p+1} + \sum_{i} v_{i,d,p+1}t_{i,d,p+1} \leq u\sum_{i} v_{ip}x_{ip} + u\sum_{i} v_{i,d,p}t_{i,d,p} \qquad \forall p \in P \setminus |P|,\ \forall d \in P \setminus |P| \tag{33}$$

$$\sum_{i} v_{i,p+1}t_{i,p+1} + \sum_{i} v_{i,d,p+1}t_{i,d,p+1} \geq l\sum_{i} v_{ip}x_{ip} + l\sum_{i} v_{i,d,p}t_{i,d,p} \qquad \forall p \in P \setminus |P|,\ \forall d \in P \setminus |P| \tag{34}$$

$$t_{ip} \in \{0,1\} \qquad \forall i, p \tag{35}$$

$$t_{ipq} \in \{0,1\} \qquad \forall i, p, q \tag{36}$$

where:

t_{ip} = binary decision variable that takes the value of 1 if stand *i* is to be first thinned in period *p*;

t_{ipq} = binary decision variable that takes the value of 1 if stand *i* is to be thinned in period *q* after it was first thinned in period *p*;

v_{ip} = the thinning volume from stand *i* in period *p* if it is first thinned in period *p*;

v_{ipq} = the thinning volume from stand i in period q if it is thinned in period q after it was first thinned in period p;

co_{ip} = the total carbon in 1,000 Mg C that accumulates in (and under) stand i by the end of the planning horizon if it is first thinned in period p ; and

cc_{ip} = the net change in aboveground carbon in stand i if it is first thinned in period p .

Constraint (29) specifies that stands, that are neither reserves nor research set-asides, can only be first-thinned at most once. Constraint (30) says that no thinning is allowed on reserves and research set-asides. Constraints (31) force stands that have already been first thinned in period p to be thinned again in a subsequent period (period q). The time window between thins is preset at either 10 or 20 years depending on whether the Thin-10 or the Thin-20 Model is used. Constraint (32) prevents the decrease of aboveground carbon across the entire forest relative to the initial carbon content (C_s). Constraints (33)-(34) control the maximum allowable increase and decrease of thinned timber volume from one period to the next. Finally, Constraints (35)-(36) define the thinning variables as binary.

(4) Optimization

All of the four three-objective models (the Basic Model, FSC-65, 85 and 105) were solved to Pareto-optimality using Tóth and McDill's (2009) Alpha Delta Algorithm. The two bi-objective Thinning Models (Thin-10 and 20) were solved with the 2-dimensional version of the same algorithm (Tóth et al.'s 2006). Both versions of the algorithm find optimal solutions by using a slightly sloped composite objective function which is a linear combination of the three functions in (2) (of two functions in the Thinning Model), and a dynamic constraint structure that iteratively restricts the search space for the integer programming solver (IBM ILOG CPLEX v.12.1, 2009). The iterative restriction of the search space is done by using the objective values of solutions from prior iterations recursively. For further algorithmic details, please refer to Tóth et al.'s (2006) and Tóth and McDill's (2009).

The bi-objective Alpha Delta uses two, while the three-objective version uses three parameters: alpha and delta in the bi-objective and alpha, delta1, and delta2 in the three-objective version. Smaller parameter settings allow the algorithm to identify a greater number of solutions, whereas larger values are helpful when only a rough estimation of the tradeoff frontier behind the objectives is needed. Alpha was set to 1 degree in both the two- and in the three-objective algorithms. Delta was set to 1,000 Mg C in the bi-objective Thinning Models, while delta1 and delta2 were set at 1/20 of the maximum achievable carbon sequestration and mature habitat values, respectively, in the three-objective Basic and the FSC Models. These settings were chosen to ensure an adequate coverage of the tradeoff frontier among the ecosystem services and opportunity costs (Fig. 2). The algorithms were implemented in an MS Visual Basic application of IBM-ILOG CPLEX v.12.1. that solved the integer programs to proven optimality. All models were formulated and solved on a Dell Power Edge R510 server that had two Intel Xeon X5670 central processing units with 3.00Gz frequency, and 32GB of Random Access Memory. The operating system was MS Windows Server 2008 R2, Standard x64 Edition.

Results and Discussion

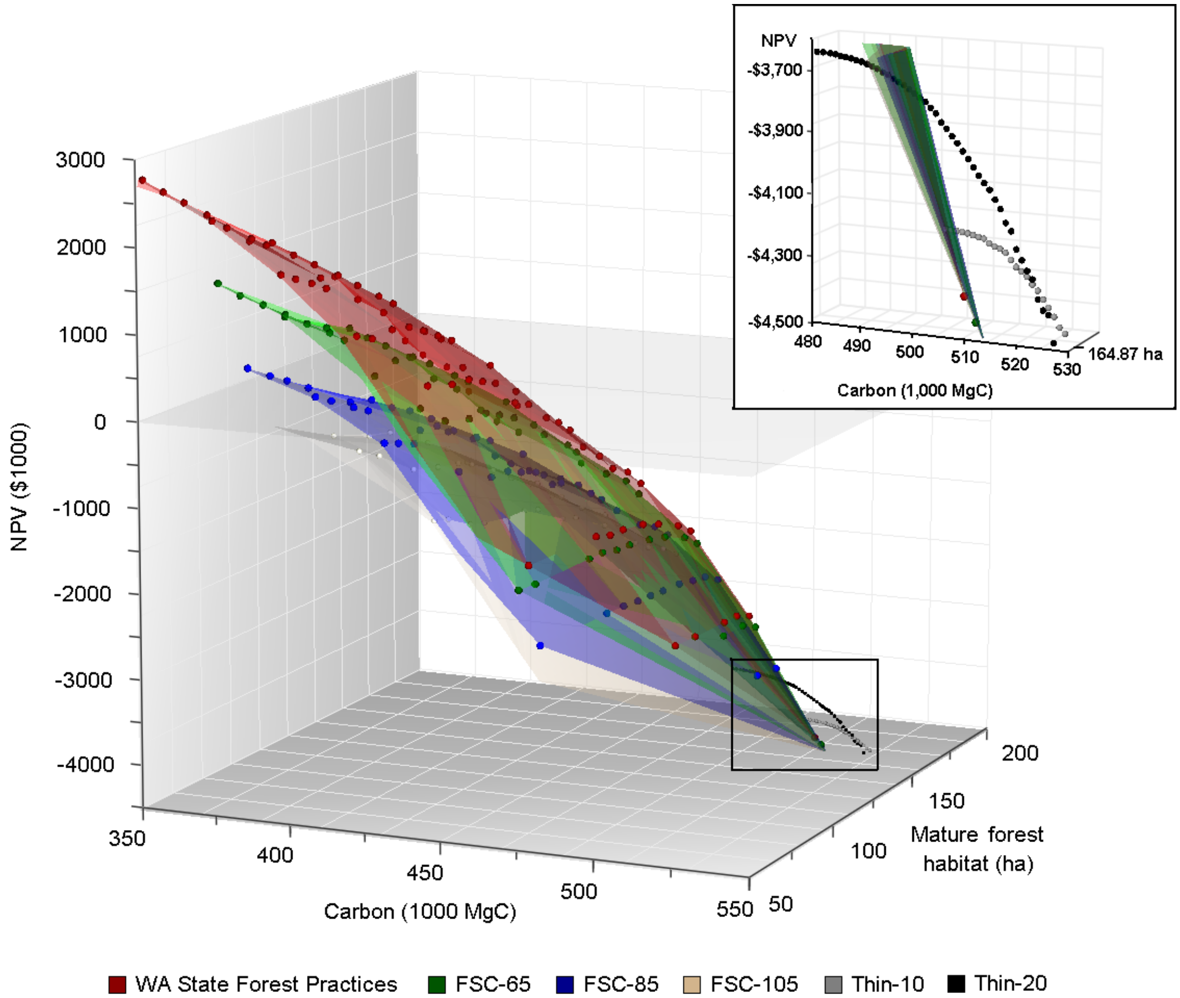
Fig. 2 maps the Pareto-optimal ecofolios for the Basic Model, the three FSC Models and the two Thinning Models in a 3-dimensional space with axes representing the three objective values that correspond to each solution. The figure depicts four distinct surfaces that correspond to the solutions (harvest plans) of the Basic Model (red) and the three FSC Certification Models (FSC-65: green, FSC-85: blue, and FSC-105: grey). The solutions to the thinning models are shown as point clouds whose mature forest habitat attributes are constant at 164.87 ha (see inset in Fig. 1): the Thin-10 solutions are in grey, while the Thin-20 ones are in black. The total computational expense of formulating and solving the models was in the range of a couple of hours on the machine whose specs are listed above.

As a reminder, the original purpose of the optimization exercise was to generate a pool of harvest plans that lead to different combinations of ecosystem services at minimal opportunity costs to the landowner. We subjected the models to different sets of rules to generate ecofolios that comply with different certification standards so that the bidders would have the opportunity to bid on “FSC-certifiable” alternatives. Pack Forest speculated that these ecofolios would be more “marketable” than those that would only comply with the State’s or the SFI’s standards. While we cannot discuss how Pack Forest would go about choosing 3-4 ecofolios (see Rabotyagov et al. (In Review) why selecting more options would not be beneficial) from the pools that are depicted in Fig. 1, we make a couple of observations in an attempt to give the reader a sense of the bundle selection process that is an organic part of the ECOSEL game.

First, we note that the red surface that corresponds to the Basic Model dominates the FSC surfaces in terms of the three objective functions that were used to define ecosystem services and the associated opportunity costs. In other words, if the landowner was to choose an ecofolio at a given opportunity cost range, solutions on the red surface would provide more of each mature forest habitat and carbon sequestration. This of course does not imply that limiting the choices to solutions from the less restricted Basic Model would be wise because FSC certification ensures some ecosystem benefits that are not explicitly accounted for in the two horizontal axes in Fig. 1. One such example is basal area retention. While this requirement is captured in the carbon sequestration and cost calculations, the retained sections of the stands were not added to the mature forest habitat patches simply because there was no way of knowing where exactly in a stand would these areas be retained. Further, some bidders might find the FSC alternatives attractive regardless of the actual ecosystem benefits that these alternatives are projected to provide. What can be concluded, however, is that the FSC ecofolios are very expensive. The more conservative our assumptions are about cMAI at Pack Forest, the higher the opportunity costs, and therefore the higher the reserve prices of these alternatives will have to be in the real auction. In fact, there are hardly a few harvest plans under the FSC-105 assumption that would allow the landowner to break even without bidder contributions (see grey surface in Fig. 1). Expensive or unaffordable ecofolios are unlikely to attract eco-investors.

The second observation that we would like to make is the result that thinning can lead to more carbon sequestration than the do-nothing management alternative (see inset in Fig. 1). For reference, the do-nothing alternative is represented in Fig. 1 by the point at which the four colored surfaces intersect the bottom plane of the graph. The reason behind the excellent "carbon performance" of thinning is that, if done correctly, it can expand the growing space of uncut trees which can, in turn, put on more growth. This additional growth can exceed the carbon loss due to the decay of the trees that are cut. That said, the thinning alternatives are very expensive to the landowner. In some cases, thinning costs more in discounted dollars than doing nothing due to the fixed operational expenses at the Forest (see inset in Fig. 1).

<u>Fig. 2</u> Pareto-optimal management plans, Pack Forest, Washington (US)



In sum, the landowner would have to be very careful in how the ecofolios are selected from the pools of solutions that were found via optimization. Some solutions might be more attractive than others in terms of ecosystem services outputs. However, these solutions are also likely to be more expensive and higher reserve prices may or may not attract enough bids. The landowner needs to manage the tradeoff between risk and reward by selecting a small subset of solutions that are broadly representative of the potentials of the resource. Offering too many ecofolios in the auction is likely to be counterproductive as the many choices could scatter the bids and lower the success rates of raising enough dollars for any given option (Rabotyagov et al. In Review).

Finally, as a caveat, we emphasize, that optimization adds to the transaction costs of ECOSEL via the extra data collection and model building efforts that are required. Too high of a transaction cost can discourage both landowner buy-in and bidding. In some cases, especially in large forests, optimization is likely to be a worthwhile exercise. In other cases, it might be unnecessary. If the property that is to be used in an ECOSEL auction is small, consisting of only a few stands, the complete enumeration of land management alternatives might be feasible manually. In ECOSEL applications beyond forestry, optimization might or might not be needed. Such cases would include bidding to decide what type of bridge or tunnel should be built over a river or to decide how a company or a power plant should be operated. Generating tangible information about the tradeoffs behind such outputs as energy production vs. pollutant emissions from a power plant, financial returns vs. outsourcing of a company, or transportation vs. environmental costs and benefits of a bridge or a tunnel, might or might not require optimization. The likely deciding factor is the scale and value of the operation.

Conclusions

In this article, we reviewed the existing research on a new, voluntary market mechanism for forest ecosystem services called ECOSEL. We showed how multi-objective optimization can be used to identify efficient management alternatives for a real forest with respect to carbon sequestration, mature forest habitat and timber revenue maximization. The primary finding of the case study is that for a set opportunity cost to the landowner, revenue maximizing harvest schedules under the Forest Stewardship Council's certification criteria are dominated by solutions that are subject to less stringent rules. The Pack Forest results suggest that cost savings associated with a successful ECOSEL auction can be substantial relative to FSC solutions that produce the same amount of carbon sequestration and wildlife habitat or less. Real auctions are necessary to confirm if cost-savings of this nature are sufficiently attractive to bidders to induce successful transactions and changes in management. It is possible that factors other than costs, or other than ecosystem services that were explicitly accounted for by optimization, play a role in how bidders choose to bid. One such factor could be the fact whether or not a particular ecofolio complies with FSC standards.

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