Computers and Operations Research 81 (2017) 119–127

Contents lists available at ScienceDirect

Computers and Operations Research

journal homepage: www.elsevier.com/locate/cor

Achieving full connectivity of sites in the multiperiod reserve network design problem

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ARTICLE INFO

Article history:
Received 30 March 2016
Revised 15 December 2016
Accepted 18 December 2016
Available online 27 December 2016

Keywords:
Reserve site selection
Reserve network design
Dynamic reserve site selection
Spatial connectivity
Mixed integer programming

ABSTRACT

The conservation reserve design problem is a challenge to solve because of the spatial and temporal nature of the problem, uncertainties in the decision process, and the possibility of alternative conservation actions for any given land parcel. Conservation agencies tasked with reserve design may benefit from a dynamic decision system that provides tactical guidance for short-term decision opportunities while maintaining focus on a long-term objective of assembling the best set of protected areas possible. To plan cost-effective conservation over time under time-varying action costs and budget, we propose a multi-period mixed integer programming model for the budget-constrained selection of fully connected sites. The objective is to maximize a summed conservation value over all network parcels at the end of the planning horizon. The originality of this work is in achieving full spatial connectivity of the selected sites during the schedule of conservation actions.

1. Introduction

Reserve network design is the problem of selecting parcels of land such that the assembled set maximizes some criterion pertaining to the conservation of species or natural communities with consideration of spatial constraints [47]. The problem is characterized by some common features that make its solution computationally challenging. First, the problem is spatially defined, where the decision criterion may be just as sensitive to where parcels occur on the landscape and their positions relative to one another as to how much land area is selected. Second, sources of uncertainty—for example, variability in land prices or acquisition budgets, errors in assessing land quality, and uncertainty about urbanization trends, market dynamics, and habitat requirements of a focal species or community—are always present and expose the decision maker to the risk of ineffective selections or missed opportunities. Third, selections are almost always carried out over time, implying that an optimal sequence of actions cannot be made without consideration of the dynamics of land availability and budget resources, and these processes are often unknown. Fourth, the decision maker may have alternatives other than land purchase (e.g., conservation easements, incentives for landowner behavior) that induce tradeoffs in costs and benefits.

The general reserve site selection problem concerns which sites to select from a pool of candidates to maximize biological benefits within a given budget. Absent any constraints regarding the spatial configuration of sites and assuming all sites have identical conservation value and cost, maximization involves a combinatorial problem of selecting p sites from n candidates, where the number of possible solutions is $\binom{n}{p}$.

The reserve site selection problem has been studied extensively, particularly in the context of a one-time decision, i.e., as a static formulation; Williams et al. [47] and Billionnet [4] provide comprehensive reviews. In practice, conservation actions are taken over time in the face of stochastic land availability, habitat loss, and budgets. Recognizing this, a few studies have addressed reserve site selection as a dynamic problem. Dynamic approaches formally acknowledge the fact that future optimal trajectories of conservation actions depend on today's action and its

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http://dx.doi.org/10.1016/j.cor.2016.12.017
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outcome; thus, evaluating the best action today requires taking into account all future actions and consequences that may occur over some specified time horizon. For this reason, such approaches explicitly account for random events related to land availability status [17,38,41], land market feedbacks [1,15,20,41], land costs [45], habitat suitability, and budget availability, among others. Others account for uncertainty in key estimated parameters, such as survival or persistence probabilities [5,27]. Stochastic dynamic programming [13,23,32,35,39], heuristic algorithms [6,18,24] and integer programming models [15,17,36,38,41] have been applied to solve these dynamic decision problems. Approximate dynamic programming [33] may be particularly useful in reserve site selection applications as exact methods quickly succumb to problem size.

Our interest is in a special subclass of this problem, the reserve network design problem (RNDP), in which a constraint of parcel connectivity is imposed. The constraints involved in finding admissible solutions of contiguous regions introduce greater complexity to the problem, compared with the reserve site selection problem.

In selecting sites for reserve design purposes connectivity of habitat is important for allowing species to move freely within a protected area. The aim of this work is to formulate an improved algorithm for the design of a network of sites for conservation purposes which maximizes some utility subject to various constraints. These constraints include a budget limitation and spatial attributes such as connectivity.

Allocating least cost Hamiltonian circuits or paths in a graph encompass various applications of real-life problems including transportation scheduling problems, delivery problems, forest planning, telecommunication and social networks, reserve network design, and political and school districting [7–9,11,12,16,21,22,34,37,44]. Each of these problems, known as a variation of the travelling salesman problem, require particular objectives and constraints to be satisfied.

Several methods have been presented for the reserve network design problem with consideration of contiguity requirements. Williams [46] formulated the first general, practical integer programming method for land acquisition that enforced full contiguity of the selected sites. The method required the specification of the number of sites to be selected. Others have also used graph theory and network optimisation [10,14,29–31] to solve the RNDP. Where budget resources were sufficient, Önal and Wang [31] considered minimizing the sum of gaps between neighboring sites to encourage a fully connected reserve. Conrad et al. [10] proposed a hybrid approach that combines graph algorithms with mixed integer programming (MIP)-based optimization for finding corridors connecting multiple protected areas together. Finding corridors required preselecting sites in the landscape to act as a source and a sink. Jafari and Hearne [19] proposed a mixed integer programming formulation of the RNDP using the concept of flow in a network. The method ensures full contiguity of both regularly (grid-based) and irregularly shaped candidate sites. The model also accommodates other forms of spatial constraint such as compactness, which is often an important property of a solution.

To our knowledge, the reserve network design problem in which a constraint of parcel contiguity is imposed has not been investigated in the context of a multi-period decision problem. That is, the making of optimal decisions with respect to which parcels to choose and the order in which to acquire and connect them may be informed by the length of the planning time horizon and assumptions about the time trajectory of budgets, parcel costs, and parcel values.

We present a model to solve the multi-period reserve network design problem where extrinsic factors (budgets, land prices, conservation values) may vary over the length of a fixed planning horizon. We demonstrate application of our model to a real reserve network design problem regarding conservation of the gopher tortoise (*Gopherus polyphemus*) in Georgia, USA. Our model provides an optimal solution that describes where to purchase parcels and in what order to acquire them for the goal of making the largest contiguous reserve possible constrained by budget. Although our solution is not stochastic, we extend the static one-shot RNDP [19] with multiple time steps, time-varying parameters, and dynamic carry-over of budget, which is a significant step toward fully dynamic representation of the problem.

Our work herein focuses on the multi-period mixed integer programming model for budget-constrained selection of fully connected sites for cost-effective conservation. The objective is to maximize a summed conservation value over all network parcels at the end of the planning horizon under time-varying conservation costs and budget. An overview of the proposed model is presented in Section 2 and the formulation and extension of the model accompanied by an example in Section 3. The study area and the focal species, as well as the design and results of applying the model to the case study, are described in Section 4. We discuss opportunities and limitations of the model, as well as areas of future research in Section 5.

2. Materials and method

2.1. Landscape representation

Consider a landscape as a graph (network) that consists of N nodes (sites) and set of arcs that link them. Each node has its own attributes such as cost and utility values. The utility value associated with each node may be a weighted average of multiple attributes that are of importance to conservation planners. The arcs define links between two nodes, representing two adjacent sites with a common boundary. In this work we will frequently refer to the flow in the network. To construct our flow network, we add a dummy node as the supply node containing the total capital available to the network. In our application, capital is represented by the total budget available. Capital can only flow along arcs, in other words, from a node to one or more of its neighbouring nodes (see Fig. 1).

2.2. Description

In our approach, we use mathematical programming techniques to build a network in a periodwise process, considering for selection at each period those parcels connected to those already chosen in previous periods. Thus, we achieve a fully connected reserve network over the planning time horizon. However, the combinatorial nature of the problem poses difficult challenges. The selection of a parcel is not based merely on the intrinsic value that it adds to the network, but also on its role as a connection to potential parts of the network yet to be acquired.

The most challenging part of the proposed method is to obtain a fully connected solution at time $t = 0$. To do so we call the flow-based model that provides the optimal "one-shot" (non periodwise) solution [19]. A brief description of that model is presented in Model 1. All the nodes of the network are involved in the solution in this static model (the constraints have been defined for every node in the network).

In this model, the decision variables and parameters are as follows: F_{ij} is a variable that indicates the flow of capital from node i (including the supply node, node 0) to node j; x_{ij} is a binary variable indicating whether or not capital flows along the arc (i, j); N_i is the set of nodes connected to node i (the adjacency set); c_i is the price value and u_i is the utility value of node i; B is the to-

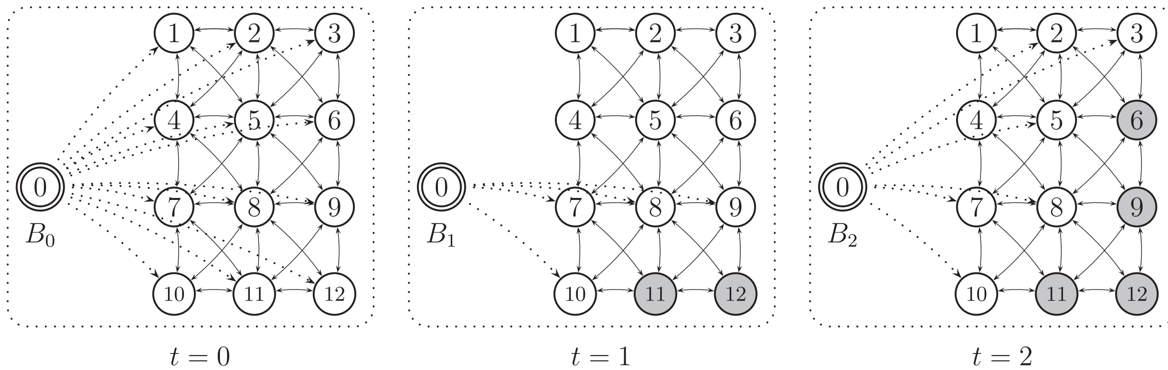

Fig. 1. A theoretical landscape is represented here as a network graph. The diagram on the left side shows the constructed flow from the dummy node (labeled "0") to all real nodes at the current period. The next diagrams represent the constructed flow from the dummy to the neighbor set of the previously selected nodes. Suppose the shaded nodes 11 and 12 have been selected at $t = 0$; then the set {7, 8, 9, 10} is the neighboring set of selected nodes at that time. Similarly, if 6 and 9 were selected at $t = 1$, then the neighboring set {2, 3, 5, 7, 8, 10} will be candidates to start flows at $t = 2$.

tal capital available for the purchase of nodes; N is the number of nodes.

Model 1: The static flow-based (MIP) model

Objective
Maximize Utility ($\sum_{i=1}^{N} \sum_{j\in N_i} x_{ji} * u_i$)

Constraints

- $\sum_{i=1}^{N} F_{0i} \leq B$
- $\sum_{j\in N_i} F_{ji} - \sum_{j\in N_i - \{0\}} F_{ij} = c_i * \sum_{j\in N_i} x_{ji}, \;\; \forall i \in N$
- $\sum_{j\in N_i} x_{ji} \leq 1, \;\; \forall i \in N$
- $\sum_{i=1}^{N} x_{0i} = 1$
- $x_{ij} \leq F_{ij}, \;\; F_{ij} \leq M * x_{ij}, \;\; \forall F \notin (0, 1)$

Decision Variables
$x_{ij} \in \{0, 1\}, F_{ij} \geq 0$

To extend the one-shot model above to the multi-period RNDP and to ensure the connectivity of all sites selected through the multiple time periods, we propose the following high level approach. At each time step after the initial one, we consider the neighboring nodes of all nodes selected at the previous time periods. We then allow flow arcs from the dummy node only to those specified nodes, and this is performed at every time period. In this manner, the model propagates the capital supply through those nodes (specified neighbor set) to the rest of the network, ensuring connection between the newly selected and the already selected nodes.

Fig. 1 visualizes the idea behind flowing capital through the network at the current period and the future. By including the neighboring set of the selected nodes for each time period, not only are we able to select nodes connected to each other but also we have the ability to input new values of the time-varying parameters of the problem, e.g., the cost of lands, or conservation-introduced amenity of the land under consideration. Deploying this idea, we developed an innovative model for the planning of conservation actions over an arbitrary time horizon. The model as presented below provides a solution for a single reserve located within a region. The method can address solving the problem in multiple (P) subregions of a large region if full connectivity across the region is not a feasible or an ideal solution.

3. The exact multi-period RNDP formulation (mp-RNDP)

In this section, we present a mixed integer program model for the multi-period planning problem with time-varying (but not dynamic) budgets, parcel costs and parcel utilities. The model selects sites that are fully connected to maximize the utility value at the end of the planning horizon. Decision variables used in the model are as follows:

F_{ijt}: A continuous variable that indicates the flow of capital from node i to node j in the time period t, $(i = 0, \cdots, N, j = 1, \cdots, N, t = 0, \cdots, T)$;

x_{ijt}: A binary variable indicating whether or not capital flows along the arc i, j in the time period t, $(i = 0, \cdots, N, j = 1, \cdots, N, t = 0, \cdots, T)$, that is;

$$x_{ijt} = \begin{cases} 1, & if\ F_{ijt} > 0 \\ 0, & otherwise \end{cases} \tag{1}$$

Parameters used in the models are as follows:

N_i: The set of nodes connected to node i including the dummy node 0 (the neighboring set);

c_{it}: The conservation cost of node i in the time period t. Cost may refer to acquisition cost (e.g., securing land for protection), management cost (e.g., ongoing stewardship, monitoring and enforcement activities on the site once it has been protected), transaction cost (e.g., negotiating agreements to protect a particular property), or a combination of all three [26]. This value may be a constant (independent of the solution of past time) or variable over time.

u_{it}: The utility value of node i; the value may be any relevant conservation metric, for example, the number of species, an index of rarity or vulnerability of species, probability of loss, connectivity (e.g., Sutherland et al. [40]), etc. This value may be a constant or variable over time.

B_t: The total capital available for conservation actions applied to sites in the time period t. Budgets are not set in a one-time lump sum amount; rather, amounts available for conservation action vary over time [13].

N: The number of nodes.

The model is formulated as follows:

$$Max \sum_{t=0}^{T} \sum_{i=1}^{N} \sum_{j\in N_i} x_{jit} * u_{it} \tag{2}$$

subject to

$$\sum_{i=1}^{N} F_{0it} \leq B_t, \quad \forall t = 0, \cdots, T \tag{3}$$

$$\sum_{i=1}^{N} x_{0i0} = 1, \quad (or \leq P) \tag{4}$$

$$x_{0it} \le \sum_{j\in N_i}\sum_{t'=0}^{t-1}\sum_{q\in N_j-\{0\}} x_{qjt'},\qquad \forall i=1,\cdots,N,\ \&\ t=1,\cdots,T \tag{5}$$

$$\sum_{t=0}^{T}\sum_{j\in N_i} x_{jit} \le 1,\quad \forall i=1,\cdots,N \tag{6}$$

$$\sum_{j\in N_i} F_{jit} - \sum_{j\in N_i-\{0\}} F_{ijt} = c_{it} * \sum_{j\in N_i} x_{jit},\qquad \forall i=1,\cdots,N,\ \&\ t=0,\cdots,T \tag{7}$$

$$x_{ijt} \le F_{ijt},\quad \forall j\in N_i \qquad \forall i=1,\cdots,N,\ \&\ t=0,\cdots,T \tag{8}$$

$$F_{ijt} \le M^t * x_{ijt},\quad \forall j\in N_i \qquad \forall i=1,\cdots,N,\ \&\ t=0,\cdots,T \tag{9}$$

$$F_{ijt} \ge 0,\quad x_{ijt} \in \{0,1\} \tag{10}$$

The objective function (2) maximizes the utility value of selected sites at the end of the planning time horizon. Note that capital flowing along the arc (i, j) implies that the sites corresponding to nodes i and j have both been selected.

Constraint (3) indicates that the supply of capital from the dummy node to the real nodes should not exceed the given budget at each time period (B_t). To ensure having only one contiguous subset of sites, Constraint (4) allows capital to flow from the dummy node to exactly one single node on a single arc in the current time period $t = 0$. If more than one contiguous region is desired we replace Constraint (4) by $\sum_{i=1}^{N} x_{0i0} \le P$ where P is the number of contiguous regions.

Constraint (5) has the main role in forcing connectivity of selected sites over time. In fact, it constructs the possible variable arcs to propagate capital from the dummy node to the neighbor set of selected sites in the previous periods of time t ($t = 1, \cdots, T$).

Constraint (6) ensures that the capital only comes into node i from one source, i.e. the corresponding node can only be purchased or visited once. It prevents reselection of nodes if they have been selected before time t.

Constraint (7) specifies that node i is selected if the capital flows to that node from the dummy node or one of its neighbors exceeds the cost of that node, where the difference flows as capital outward from the node.

Constraints (8) and (9) contain logical expressions between the continuous variable F and the binary variable x as x_{ijt} is zero unless capital is flowing from node i to node j at the time period t as expressed by equation (1). The coefficient of x_{ijt} in the right side of Constraint (9) is the well-known Big-M coefficient which could be any large number. We assign it to the largest possible value for F_{ijt}, that is, $M^t = B_t$.

3.1. Extension to dynamic parameters

In many conservation settings, drivers such as climate change or the purchase actions themselves may be expected to induce dynamic behaviors in parcel costs or biological utility. Through the introduction of additional constraints, our model can be extended to accommodate dynamic relationships while maintaining spatial connectivity. For example, if cost is represented as a dynamic variable, then rules governing its dynamic behavior would be added as constraints to the model: $c_{i,t} = c_{i,t-1} * (1 + r) + \delta(t, i)$ where the constant r is the expected rate of increase or decrease on the cost value each year and $\delta(i,\ t)$ is a time and parcel-specific function that shows the effect of the selected sites at the previous time on this stage [41]. Although the inclusion of such a constraint introduces a nonlinearity to the model, Toth et al. [41] demonstrate that the constraint can be linearized. In addition to the cost value, the annual budget could be calculated dynamically as when, for example, carry-over of funding between planning periods is allowed in the process. Carry-over dynamic budget can be included in our model above by adding the following constraint:

$$B'_t = B_t + \left(B'_{t-1} - \sum_{i=1}^{N} F_{0it-1}\right),\quad B'_0 = B_0 \tag{11}$$

where B'_t is the budget allocation in period t plus the unused amount of budget carried over from period $t - 1$.

3.2. An example

Assume a landscape contains 25 sites and is to be planned over a five-year period in the interest of conservation purposes. The table in Fig. 2 shows the numerical data attached to each of the 25 sites of the example. The numbers attached to each site refer to the biological value (utility) and the economical parameter representing site cost. We assume that the utility value is a known and fixed constant for the entire planning time horizon and that cost is a certain value but variable for each year (the second line of each cell contains five different numbers showing the cost of the site for each year respectively). Furthermore the budget differs annually, given by year as: 8, 10, 9, 9, 8.

Below the table are two rows of grids that indicate the result of applying two versions of the RNDP model on the example. The first row of grids represents the result of the Exact Multiperiod RNDP model, captioned from a to e in respect to differing length of the planning time horizon (range 1–5). The second row of grids represents the result of a heuristic alternative model captioned from f to j. The outcome of applying both models on the example exposes the performance of them explicitly. The two approaches differ in how time is treated in the optimization, and the consequence of this difference is apparent in the solutions.

Under the heuristic approach, we view the problem as a multistage optimization problem that is decomposed into subproblems for each year. This decomposition results in a significant reduction of computational complexity in comparison with the exact Multiperiod model. We plan for each year over a 1-year time horizon rather than over multi-year terms. This model allows us to solve each subproblem statically at each stage by constructing a relationship between stages. Because the full connectivity of sites (parcels) at the end of planning time horizon is the main concern of this work, we are required to keep track of the selected sites at each stage and specify the sites adjacent to them. Thus we solve the problem at the next stage linked to the solution of the previous stage (the neighboring set of previously selected nodes). Because the heuristic model solves the problem as a sequence of 1-year subproblems, the network at $T + 1$ contains the subset of sites already chosen by time T. Importantly, extending the time horizon has no impact on the decisions the heuristic approach takes for earlier time periods. On the other hand, the exact model solves the entire multiperiod problem from scratch for any planning time horizon presented. Thus, the network at the Tth year of an optimal solution with $T + 1$ year planning horizon may not resemble the network at the same stage of an optimal solution with T-year planning horizon. That is, the exact solution emphasizes the importance of selection with respect to the time horizon. For this reason, the exact model searches over a larger decision space than

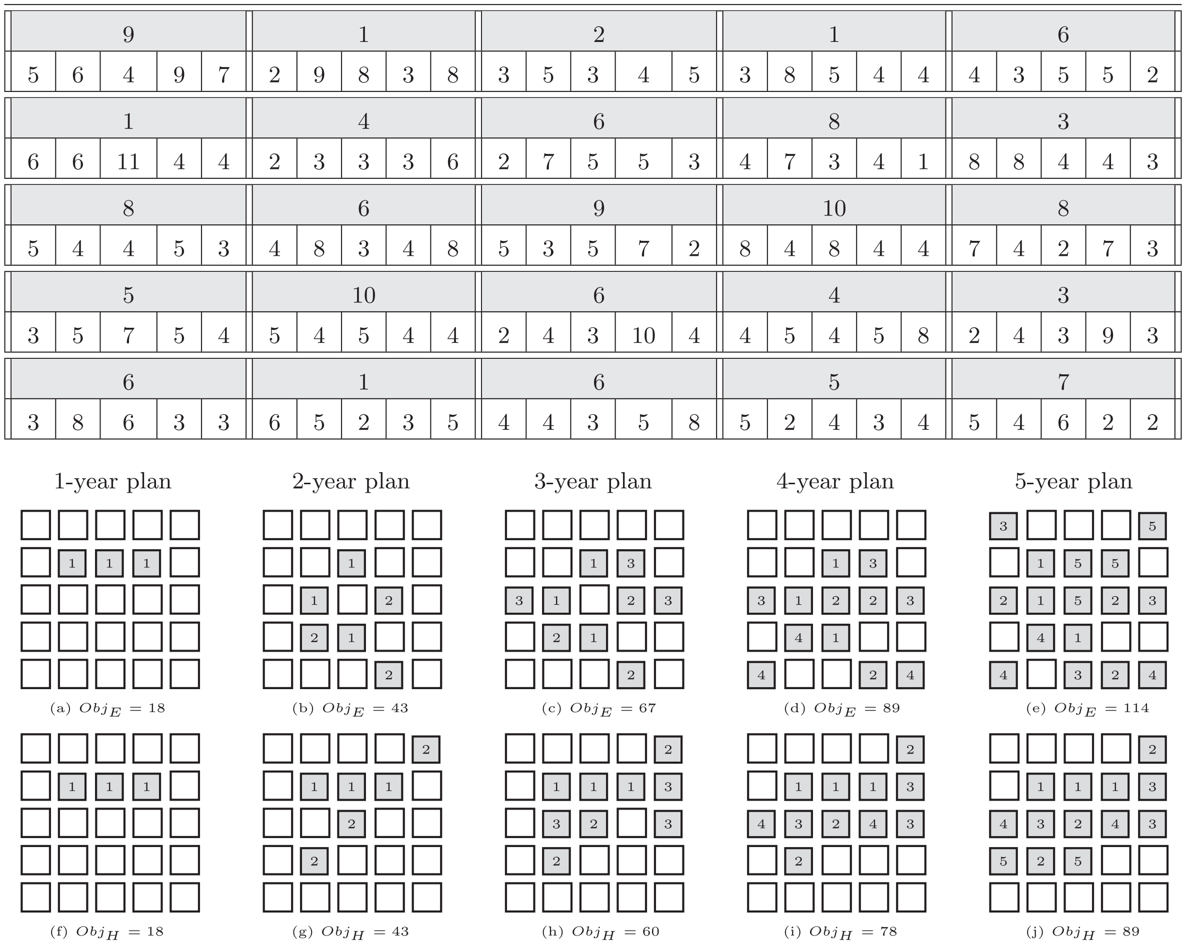

Fig. 2. (Above) Biological value (shaded cells) and time-varying parcel cost (white cells) for parcels arranged in a 5 × 5 parcel landscape. (Below) Year (shaded) in which the corresponding parcel was selected. For example, 2 represents selection of the site in year 2, 4 represents selection of the site in year 4, etc. Grids (a)–(e) are solutions corresponding to the exact Multiperiod RNDP model applied to different planning time horizons (1–5 years). Grids (f)–(j) are solutions corresponding to a heuristic alternative model that decomposes the problem into subproblems for each year. Obj_E and Obj_H are the aggregated utility value of the selected sites at each planning time horizon for the exact model and the heuristic model, respectively. Note that in this grid example we count corner nodes in the adjacency set of each node, resulting in each node having 3, 5, or 8 neighbouring nodes.

does the heuristic model, leading the exact model to discover more cost-effective solutions.

4. Case study

4.1. Focal species and habitat definition

The gopher tortoise is a long-lived, largely fossorial inhabitant of pine forests in the coastal plain of the southeastern US. It has faced population declines across its range due to losses of habitat and exploitation by humans. It has been declared Threatened [42] in the western portion of its range and thus receives federal protection there. In the remainder of the range, state conservation agencies retain management authority over the tortoise; however, these agencies are highly motivated to prevent further expansion of federal legal status and the subsequent encumbering of costs and restrictions related to species recovery. In Georgia, managers within the Georgia Department of Natural Resources (DNR) wish to enact conservation measures that may forestall or eliminate need for federal protection. As habitat needs of the tortoise are so specific (described below), DNR and its partners are exploring the acquisition of lands, either through purchase or easement, for the formation of reserves. Gopher tortoises exist as metapopulations on the landscape [25]; therefore, reserves must be both large and contiguous in order to facilitate interchange of individuals among subpopulations.

The tortoise's basic habitat requirements are straightforward: sandy soil that does not experience excessive flooding or ponding, and sufficient accessible forage in the form of forbs and grasses [3]. But because ground layer vegetation is difficult to classify via remotely sensed data, whereas soil attributes are available through the SSURGO database [28], we define suitable habitat exclusively in terms of soil [43]. Areas of good soil that do not currently support tortoises may do so in the future, with restoration and appropriate management of vegetation, for example via frequent controlled burning [2].

4.2. Study area

Broadly our study area was the US state of Georgia south of the Fall Line (i.e., the coastal plain ecoregion) where soils suitable for gopher tortoise burrowing are located. The study area is dissected by major barriers to tortoise movement (e.g., unsuitable soil, roads, and large rivers), resulting in demographically separated regions. We selected one such region in west-central Georgia for this case study (Fig. 3). This region includes large Department of Defense lands, private timberland and agricultural lands, and several small towns.

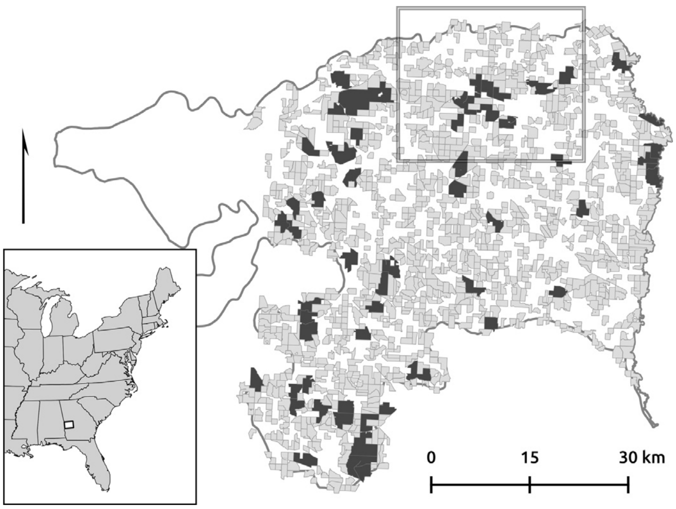

Fig. 3. Land parcels occurring in the west-central Georgia, USA, study region (for clarity, only parcels $\geq$ 61 ha displayed). Gopher tortoises in this region (denoted by the dark gray boundary curve) are demographically isolated from populations outside the region due to barriers to their movement (roads, large rivers, unsuitable habitat). Each darkened cell indicates a candidate seed parcel ($\geq$ 324 ha) for serving as a nucleus for reserve construction. In all of the optimization scenarios described below, the model provided optimal reserve networks starting from a seed parcel identified in the north part of the region (boxed area; see Fig. 4).

Parcels (ownership boundaries) were obtained from each county and merged with public lands derived from the Protected Areas Database (PAD-US version 1.3 downloaded from gapanalysis.usgs.gov, 1 Sep 2014) and compiled into a single database. Requiring reserve contiguity among parcels necessitated identifying a neighbor set of nodes for each focal parcel. We expanded our definition of neighboring parcels to better match the ability of gopher tortoises to cross roads with light traffic, utility rights of way, or other narrow landscape features that could separate two nearby parcels. Parcels were not required to share a boundary to be considered neighbors; their boundaries had only to come within 100 m of one another. For such noncontiguous neighbors, we estimated the shared boundary length as one-half the perimeter of the intersection of 50-m buffers around each parcel.

Following removal of very small parcels ($<$ 16.2 ha) that were impractical to consider for acquisition, the resulting data set used in analysis comprised 4041 parcels that included attributes on utility, identities of all neighboring parcels, and lengths of shared boundaries. Parcel utility was estimated as the area of potentially suitable habitat within the parcel. To determine potentially suitable habitat within each parcel, NRCS SSURGO soils data were reclassified into Suitable and Unsuitable based on suitability ratings developed by the U.S. Fish and Wildlife Service and the Natural Resources Conservation Service [43].

4.3. Reserve planning assumptions

For the case study, we assumed that DNR would conduct all parcel acquisition over a 5-year planning horizon. We also assumed that the agency's objective would be to maximize total amount of suitable habitat at the end of the planning horizon within budget limitations and in a way that maintains parcel connectivity at every stage of decision making. The DNR will likely approach reserve construction by acquiring one seed parcel of very large size then successively acquiring neighboring parcels that exceed a minimum size. We selected 324 ha as the seed parcel size threshold and 81 ha as the size threshold of subsequent acquisitions, values which approximate the thresholds DNR is likely to consider. To address the first spatial requirement regarding minimum size of the seed parcel, we modify the proposed mp-RNDP model (in Section 3) to construct the initial flow from the dummy node only to the nodes that exceed the desired minimum size of 324 ha. The following constraint forces the model to choose among seed parcels:

$$x_{0i0} * (area_i - minSeedSize) \geq 0 \tag{12}$$

To accommodate the second spatial requirement regarding minimum size of successive parcels, we assume a desired size threshold and add a constraint to meet it as follows:

$$(area_i - SizeThreshold) \sum_{j \in N_i} x_{jit} \geq 0 \tag{13}$$

This constraint forces the model to select among sites that exceed the parcel size threshold.

Fifty-five potential seed parcels totaling 27,623 ha exist in our study landscape. Under the 81-ha purchase threshold, 841 parcels totaling 133,230 ha were candidates for acquisition. These parcels averaged 2.7 neighbors per parcel (maximum 10 neighbors), and mean length of shared boundaries was 938 m. The candidate parcels form 139 connected components, 19 of which contained a seed parcel.

4.4. Cost and budget scenarios

To assess behavior of the proposed model in Section 3 under varying conditions, we considered three scenarios representing plausible constraints on parcel acquisition by DNR. Based on recent budgetary history, land transaction information, and average land costs provided by DNR (M. Elliott and S. Friedman, Georgia Department of Natural Resources, personal communication), we adjusted land costs and annual budget conditions in the following ways:

Scenario 1: Low, fixed budget ($4 M per year), high land cost ($5,016/ha)
Scenario 2: High, fixed budget ($7 M per year), low land cost ($4,522/ha)
Scenario 3: Time-varying budget with low average (mean $4 M), high land cost ($5,016/ha)

In Scenarios 1 and 2, the budget is assumed fixed, thus the amount available to the agency each year is known in advance. The sum of the annual budgets represented 3.0% and 5.8% of the total value of all available parcels in Scenarios 1 and 2, respectively. In Scenario 3, the budget varies through time. A planner who does not know budget amounts in advance may consider replicating random budget streams under our deterministic model. For the last scenario, we drew random deviates from a lognormal distribution with mean $4.0 M and standard deviation $0.496 M (yielding a 95th percentile of $8 M) for each year of the planning horizon. We conducted the optimization for five budget realizations for Scenario 3, and we interpreted the mean results (the realizations of random budget values are found in Table 2 in the row of "Budget" under columns labeled "no-C/O").

All scenarios above assume that budget funding cannot be carried over from one year to the next. We investigated the potential of the ability to carry over funding to achieve greater conservation value. We conducted a "carry-over" version of each Scenario 3 run by applying the additional model (Constraint (11)).

To demonstrate performance and efficiency of the model when challenged with a greater number of candidate solutions, we ran Scenarios 1–3 a second time after reducing the minimum parcel size threshold from 81 to 61 ha. Under the reduced threshold, 1298 parcels totaling 165,647 ha (increasing from 841 parcels totaling 133,230 ha) were candidates for purchase. Mean number of neighbors per parcel increased to 3.2 (maximum 13 neighbors),

Table 1
Objective value, the associated optimality gap, and solution times of 3 case study scenarios run under each of two acquisition size thresholds.We use ILOG CPLEX 12.6 with ILOG Concert Technology for C++ on an ordinary desktop. Each optimization was allowed to run to completion or to a maximum of 48 h. Note that the default value of the relative MIP gap tolerance is 1e−4.

Scenario	Threshold 81 ha			Threshold 61 ha		
	Obj. Value (ha)	Optimality Gap	Solution time	Obj. Value (ha)	Optimality Gap	Solution time
$S1$	3345	0.0%	21 h	3442	0.0%	48 h
$S2$	5823	0.0%	2.5 h	6014	0.0%	33 h
$S3_1$	2568	0.0%	5 h	2628	2.5%	48 h
$S3_2$	3116	0.0%	3 h	3187	0.0%	11 h
$S3_3$	3781	0.0%	6 h	3827	1.9%	48 h
$S3_4$	4547	0.0%	22 h	4639	4.9%	48 h
$S3_5$	2485	0.0%	13 h	2540	0.0%	29 h
Mean	3299.4	- - -	9.8 h	3364.2	- - -	37.9 h

Table 2
Stage-wise results of the mp-RNDP model for five realizations of Scenario 3 contrasting the classes of no budget carryover (”no-C/O”) and budget carryover allowed (”C/O”), enforcing a minimum acquisition size of 81 ha and applied over a 5-year planning horizon. At each stage within the planning horizon (column year), the amount of capital allocated (budget), consumed (spent) and remaining (unspent) are displayed. Both classes begin with the same initial budget, and both receive the same budget amount per year. However, funds that are not spent each year are forfeited under “no-C/O” whereas they remain available for future use (carried over) under “C/O”. Shading in the body of the table highlights circumstances under “C/O” in which the entire budget allocated for the year is carried over to the next year.

Time	Budget	$S3_1$		$S3_2$		$S3_3$		$S3_4$		$S3_5$		Mean	
Period	Status	no-C/O	C/O	no-C/O	C/O	no-C/O	C/O	no-C/O	C/O	no-C/O	C/O	no-C/O	C/O
	Budget	4171	4171	2122	2122	4591	4591	5658	5658	4119	4119		
0	Spent	4138	1758	1968	1656	4397	3682	5618	1968	4071	3264		
	Unspent	33	2413	154	466	194	909	40	3690	48	855		
	Budget	3308	5721	5278	5744	6261	7170	3096	6996	1973	2828		
1	Spent	3272	**0**	5271	3627	6253	5940	3061	**0**	1968	**0**		
	Unspent	6	5721	7	2117	8	1230	35	6996	5	2828		
	Budget	2269	7990	4188	6305	4225	5455	9780	14808	1772	4600		
2	Spent	2249	5025	4176	5108	4134	2117	9750	**0**	1714	3627		
	Unspent	20	2965	12	1197	91	3338	30	14808	58	973		
	Budget	2504	5469	4943	6140	2688	6026	6030	20838	2436	3409		
3	Spent	2454	3627	4908	2144	2671	640	6025	10345	2290	1758		
	Unspent	50	1842	35	3996	17	5386	5	10493	146	1651		
	Budget	3322	5164	2033	6029	4644	10030	2953	13446	4605	6256		
4	Spent	3130	5086	1911	6009	4630	10008	2927	13436	4467	6166		
	Unspent	192	78	122	20	14	22	26	10	138	90		
Total Unspent		331	78	330	20	324	22	136	10	395	90	303	44
Obj. Value (ha)		**2568**	**2677**	**3116**	**3186**	**3781**	**3806**	**4547**	**4571**	**2485**	**2559**	**3299**	**3360**

and mean length of shared boundaries reduced to 816 M. The reduced threshold resulted in fewer singletons (30) than before, and fewer groups with 1 or more connecting neighbor (47). Of the connected groups, 10 contained a candidate seed parcel. The sum of the annual budgets in Scenarios 1 and 2 represented smaller portions (2.4% and 4.7%, respectively) of the total value of all available parcels under the reduced threshold.

For all scenario runs (shown in Table 1), we computed the objective value (area of suitable habitat), solution time, and optimality gap.

4.5. Results

The effect of a larger budget and cheaper land on reserve design is visually (Fig. 4) and quantitatively evident (Table 1) in a comparison of outcomes of Scenarios 1 and 2. Under the minimum acquisition threshold of 81 ha, Scenario 2 returned 74% more habitat than did Scenario 1. Under the minimum acquisition threshold of 61 ha, the corresponding comparison was almost the same (75%).

Despite equal mean annual budgets provided in Scenarios 1 and 3, uncertainty in annual budget translates into an expected loss of objective value. The expected return under Scenario 3 was 1.9% less than that under Scenario 1 for the minimum acquisition threshold of 81 ha (Table 1).

By expanding the solution space through relaxation of the minimum acquisition threshold (from 81 to 61 ha), greater values of the objective can be achieved. For Scenarios $1-3$, the improvement in objective value was 3%, 3%, and 2%, respectively.

However, accommodating a larger search space comes with added computational burden, sometimes necessitating a termination of the algorithm before an optimal solution can be achieved. The optimality gap (Table 1) measures the discrepancy between the realized solution and the optimal solution as a percentage of the optimal value. For both thresholds of minimum acquisition size, optimal solutions for Scenarios 1 and 2 were found within two days of run time. Similarly, optimal solutions for all cases of Scenario 3 were found within two days of run time for the minimum acquisition threshold of 81 ha. However, for the threshold of 61 ha, optimal solutions were not discovered in three cases of Scenario 3, even after two days of run time for some cases. But in all three cases, the optimality gap was reasonable, ranging from 2% to 5%.

The ability to carry over budget funding from one year to the next offers the flexibility to spend funds efficiently in the future. Viewing the spending activity on a year-by-year basis (Table 2) illustrates how carry-over may be exploited to obtain greater value in future acquisitions. For example, classes “no-C/O” and “C/O” started from the same initial budget amount of $4.171 M for realization 1. However, under class “C/O”, less than half of that amount was spent in the first year, and none of the accumulated amount was spent in the second year (Table 2). In doing so, larger investments were possible later in the time frame than were possible

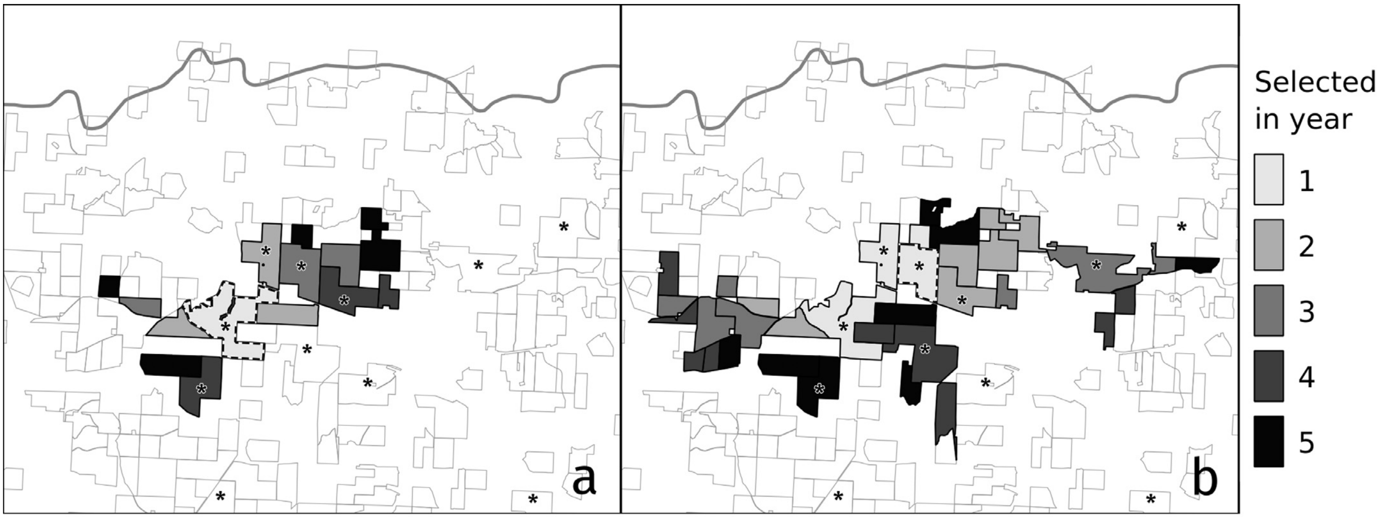

Fig. 4. Optimal acquisition schedules for the construction of a contiguous reserve under two financial scenarios: (1) fixed budget of \$4 M per year and land cost of \$5,016/ha (panel a) and (2) fixed budget of \$7 M per year and land cost of \$4,522/ha (panel b). Parcel shading indicates order of acquisition. The seed parcels indicated here (broken outlines) were selected by the model from among candidate seed parcels ($\geq$ 324 ha; denoted '⋆') distributed across the region at large (Fig. 3). In both optimization scenarios, parcels of $\geq$ 81 ha that adjoin the network are eligible for acquisition. Therefore, only parcels $\geq$ 81 ha are displayed.

under "no-C/O". Consequently, the value of the total investment by the end of the time frame was greater under "C/O" than under "no-C/O", and fewer funds were forfeited. On average, the objective value under "C/O" was 2% greater than that under "no-C/O", and "C/O" forfeited 85% less budget than did "no-C/O". We note that if the client indicates that part of the budget (<100%) must be spent at each period, Constraint (11) can be modified to meet this requirement.

Across all scenarios and parcel size thresholds, the selected reserves occurred in the same geographic region of the study area (Fig. 4). This spatial concordance derives entirely from the characteristics of the parcels in that region (large, well connected, with high proportion of tortoise habitat). We emphasize that all seed parcels (dark gray in Fig. 3) were equally available to be chosen as the initial node under each scenario.

5. Discussion

We generalized the approach of [19] for building spatially contiguous reserve networks by allowing successive acquisitions to be optimally sequenced over a planning time horizon. We developed this method in the application context of varying budget resources, action costs, and rewards. To our knowledge, this has not been addressed by any other work. To implement the method, we developed a mixed integer programming model which derives a bona fide optimal solution. An added novelty of the models is the ability to accommodate irregular shapes of sites and in the ability to update dynamic parameters.

Due to the combinatorial structure of reserve network design problems, the time complexity of the proposed mp-RNDP model rises exponentially with both the planning time horizon (T) and the size of the problem (the number of edges or adjacencies between parcels). The space complexity of the model is linear in both the number of edges and the length of the planning time horizon.

Because the model's performance is so sensitive to problem size, we investigated heuristic alternatives that provide near-optimal solutions at a fraction of the computational cost. We envision one strategy of decomposing the problem into subproblems on each stage that are easy to solve and linking the solutions through time (described in Section 3.2). For instance, we ran the heuristic stagewise version of the model on our data under Scenario 1 for the minimum acquisition threshold of 81 ha. We obtained a sub-optimal solution yielding an objective value of 2902 ha, which is 86.76% of the optimal solution of the multiperiod solution. The heuristic version ran very quickly (25 min; 98% time reduction) compared to 21 h for the exact version.

We described the model and presented the case study based on fee-purchase as the only means of acquiring parcels. However, we may enrich this model by addressing not only the site to be protected but also the optimal mode of protection. Through the introduction of a decision variable with more levels, the model may be extended to include other forms of conservation acquisition, including conservation easements or landowner incentive payments on privately held land. Thus, trade-offs between conservation efficacy and cost of the action could be formally evaluated for a set of alternative actions.

As is evident in Fig. 4, the model may produce solutions that a conservation agency may consider to be overly dendritic on the landscape. That is, the model in current form lacks any means to achieve compact spatial arrangements with low area/perimeter ratio. Two strategies described by [19] are applicable in this model. The first acts on the definition of arcs that connect nodes. Greater compactness may be achieved by dissolving arcs corresponding to boundaries between neighboring units that do not exceed a threshold length. The other strategy acts directly on the objective through the incorporation of a component that minimizes the perimeter of the assembled set.

One future area of research in regard to conservation planning for gopher tortoise concerns building into the purchase price a stewardship fund that pays for long term habitat management of the site. Ongoing management that maintains suitable vegetation conditions is a critical requirement for any site that is to serve as a reserve. In most areas, this entails the application of prescribed fire to keep the forest midstory suppressed and to promote the production of ground forage. However, fire may be impractical in areas nearby to human population centers or to critical infrastructure. Suitable understory conditions may be maintained by means other than fire (e.g., mechanical disturbance, herbicide application) but usually at greater cost per hectare. Therefore, we expect a site's value as indicated by soils to be inversely related to proximity of urbanization because of higher expense required to maintain habitat in suitable conditions. Thus, the optimal spatial configuration of a reserve on a human-populated landscape should be expected to be sensitive to whether management costs are accounted for in purchase price.

Acknowledgments

We thank Angela Fuller for a review of the manuscript and for suggestions that improved the work. This project was sponsored by the U.S. Department of the Interior, Southeast Climate Science Center and the U.S. Geological Survey Southeast Ecological Science Center through the Georgia Cooperative Fish and Wildlife Research Unit, (Research Work Order 115, Cooperative Agreement G13AC00230). The Georgia Cooperative Fish and Wildlife Research Unit is jointly sponsored by U.S. Geological Survey, the University of Georgia, U.S. Fish and Wildlife Service, Georgia Department of Natural Resources, and the Wildlife Management Institute. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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