Optimum Selection of Clustered Conservation Areas for Species Relocation

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Abstract:
Much of the last remnants of suitable habitat areas for many rare, threatened, or endangered species in the U.S. are in the vicinity of military installations. The need for new and conventional training requirements is stronger than before and leads to an increased pressure to manage federal lands by balancing competing objectives and land uses. This paper introduces linear integer programming formulations for the relocation of multiple populations of a species at risk to clustered conservation areas within the boundaries of a military installation. We present a basic clustered relocation model and extend the model to minimize the distances of relocation, and to impose meta-spatial clustering on the selected areas. We introduce two methods for meta-spatial clustering, first using a constraint and second using a multi objective function. We apply the models to a dataset related to Gopher Tortoise (GT), a key stone species currently considered 'at risk', at Ft. Benning Georgia and analyze the results.

Keywords: reserve design, clustered site selection, spatial optimization, integer programming, species relocation.

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1 Introduction

Much of the last remnants of suitable habitat areas for many rare, threatened, or endangered species in North America are in the vicinity of military installations in the U.S. While some habitat deterioration may have been caused by military training, it is often argued that the military control actually prevents those areas from destructive urban and agricultural development. Besides isolation of the lands from alternative economic uses, the Department of Defense (DoD) allocates a significant amount of human capital and land for conservation efforts toward protecting and managing wildlife habitat in and around military installations. In 2006, the DoD spent \$4.1 billion on environment related expenses of which \$1.4 billion was for environment restoration and \$204.1 million was for conservation [1]. On the other hand, new and conventional training requirements increase the importance of military lands and the pressure to manage federal lands in the best possible way to balance these competing objectives and land uses. As an alternative to costly arrangements, such as purchasing land or acquisition of property rights, more effective utilization of the existing lands for conservation and military purposes can be accomplished by designing an optimum landscape that best addresses conservation and military training area needs. This paper explores alternative optimum land use strategies by incorporating various ecologically important considerations along with military training requirements.

The land use decision problem described above can be solved using optimization methods. The specific problem may be different from one case to another depending on unique characteristics of each installation in terms of military training and environmental/ecological needs. In this paper we consider a particular military installation, namely Ft. Benning in Georgia. Ft. Benning currently has an extensive population of Gopher Tortoise (*Gopherus polyphemus*), referred to as GT, and Red Cockaded Woodpecker (*Picoides borealis*), referred to as RCW, both listed as species at risk. The RCW is federally endangered and the GT is listed as a species at risk. Ft. Benning is currently undergoing an expansion of its mission, and new firing range and maneuver areas are being constructed for emerging needs. In an effort to best manage the GT and the RCW populations, Ft. Benning is looking into the optimal selection of habitat areas that can be made available for the protection of these two species. Some of the proposed new training areas are heavily populated by GT's (see Figures 1.b and 2.a); therefore the land managers are considering relocating GTs to lesser used areas to be selected within the boundaries of the installation.

In this paper the term 'Conservation Management Area (CMA)' is used to refer to a conservation reserve, a designated tract of land on which military activities are normally less intense and the land is better suited for use as GT habitat. All such areas will still be available for appropriate military training use; however these areas will be selected so as to be among the least disturbed areas. A 'CMA network' refers to a collection of multiple CMAs that together serve the conservation purpose. Since GT is a ground-bound species, the selected areas should be as 'compact' as possible, preferably 'contiguous', in order to allow movement of GT in the protected areas and facilitate interaction within and among individuals in those areas. A compact CMA would also be easier to fence, if needed. Furthermore, it would be desirable to minimize the relocation movement distances and also to have the CMAs to form a clustered network in close proximity to each other in order to promote interaction between multiple populations[1]. We

[1] In some cases habitat areas are desired to be far enough to maintain independence and minimize the risk of outbreak of diseases. With appropriate modifications, the model can incorporate this consideration.

determine optimal relocation of the affected GT populations from the areas that will be most heavily affected by the additional military training demands.

In light of the discussion above, specifying the most suitable CMAs must involve various important spatial considerations including the following: i) each designated CMA must have a minimum size, either specified in terms of the land area or in terms of the GT population aimed to be protected in that CMA; ii) each CMA should preferably have a compact (circular or square-like) shape; iii) the relocation distances should be minimized to facilitate relocated GT's adaption to their new habitat, iiv) if multiple CMAs are to be configured, they must be close to each other in order to promote interaction between multiple populations. For this purpose we develop four linear mixed-integer programming models that address the above issues. As will be elaborated in the next section, the models are largely similar; yet they have distinct features that are needed to reflect the above spatial requirements considered in site selection. The models are applied to data from Ft. Benning and the empirical results of our analysis are presented together with a discussion of the results.

2 Materials and Methods

The current evaluation is essentially identical to that involved in the design of "reserves" for protection of certain sensitive species, where the use of mathematical models goes back to the late 1980's[2] [2]. The use of the term "reserve," however is not appropriate when dealing with military installations, where protection of certain species and considerations for their management are always subject to mission requirements and Congressional authority. Therefore

[2] Initial studies used mostly heuristic methods for this purpose [3-7]. Heuristic procedures may occasionally yield optimum solutions, but more often they lead to significantly suboptimal outcomes [7 – 10].

we use the term "CMA" with regard to the application and the term "reserve" with regard to the theoretical modeling analysis. In its simplest form, the reserve design problem is stated as selecting a minimum number of habitat sites that contain populations of a specified set of species, or maximizing the number of species that can be protected under a conservation budget constraint or area limitations. Both problems are formulated as linear integer programs (IP), being special cases of the prototype 'set covering' problem and the 'maximal covering' problem[6, 7, 11 – 17]. Typically, both types of optimum site selection models result in highly sparse and dispersed reserve configurations. Recognizing this deficiency, several integer programming models have been developed in recent years to incorporate various forms of spatial considerations, such as reserve connectivity, compactness, fragmentation, buffer zones, etc.[18 – 26; see 27 for a review]. This type of consideration generally requires a much more complex mathematical formulation and large-scale models. As discussed earlier, in the problem addressed here, spatial coherence of the designated GT CMAs is particularly important. We present alternative formulations below each incorporating a different spatial criterion to determine an optimal assignment of areas to conservation based on the site characteristics (habitat suitability) and geographical locations.

The models that will be presented below have a common feature in that they consider a grid partition which comprises of square land parcels[3], each of which will be referred to as a 'site'. Each site is assumed to be an independent decision unit. When selecting sites to configure a CMA the locations of individual sites relative to other selected sites and their contributions to the conservation of GT are taken into account simultaneously. More specifically, a CMA is

[3] The square-cell assumption is not restrictive. The approach developed here can be applied to other geometric forms, such as triangles, rectangles, polygons, or even irregular forms.

characterized by a central site and a set of sites packed (clustered) around that central site. The problem is then to determine the central site of each CMA and assignment of individual sites to the CMA in an endogenous way while satisfying the conservation requirements and considering alternative spatial criteria in cluster formation[4]. For each specification of the spatial criteria considered in site selection, we formulate a linear integer program. The procedures and algebraic details of the models are described explicitly below.

We denote the set of all sites by L and denote individual sites by $k, l, m \in L$. Site selection and assignment to a CMA is represented by a binary variable X_{lk}, where $X_{lk}=1$ if site k is selected and belongs to the CMA centered at site l and $X_{lk}=0$ otherwise. Note that by construct $X_{ll}=1$ for all central sites l, i.e. the central site of each CMA must belong to that CMA. We also note that sites in the most heavily used military training areas (existing or new) are not considered for inclusion in any CMA, therefore we set $X_{lk}=0$ if site k is part of a training area. The symbol d_{lk} denotes the distance between site l and site k, and e_k denotes the existing population of GT in site k. The number of CMAs to configure is denoted by n; which is specified exogenously, but varied when designing alternative optimal configurations. Each CMA is required to sustain a minimum GT population, denoted by p. Finally, the total GT population in all the selected areas is represented by tp.

2.1 Base Model

We first address the problem of constructing n compact CMAs, each covering a minimum sustainable GT population and collectively covering a desired GT population. Here we define

[4] This model is an extension of classic p-median problem [28]. Similar models for clustering have been used previously in the literature of reserve design, business districting and political districting [21, 27].

compactness of a CMA as the overall ‘closeness’ of all sites in it. We measure this by the sum of distances from all sites to a central site in each cluster, which must be minimized to the extent possible[5]. An algebraic model that serves this purpose, which will be referred to as the ‘*Base Model*’ from here on, is given below.

$$\text{Minimize} \quad \sum_{l} \sum_{k} X_{lk} * d_{lk}$$

s.t.:

$$\text{i)} \qquad \sum_{l} X_{ll} = n$$

$$\text{ii)} \qquad \sum_{l} X_{lk} \leq 1 \quad \forall k$$

$$\text{iii)} \qquad \sum_{k} X_{lk} * e_k \geq p \quad \forall l$$

$$\text{iv)} \qquad \sum_{l} \sum_{k} X_{lk} * e_k \geq tp$$

$$\text{v)} \qquad X_{lk} \leq X_{ll} \quad \forall l,k$$

$$X_{lk} = 0,1 \quad \forall l,k$$

The objective function involves the distances from individual sites in each CMA to the ‘center’ of that CMA, which in turn is summed over all CMAs. Constraint i) ensures that n CMAs are created. Constraint ii) states that each site can belong to at most one CMA centered at some site *l*. Constraint iii) requires that each CMA supports a population that exceeds the minimum sustainable size[6], while constraint iv) ensures that all CMAs collectively support a desired total population. Finally, constraint v) implies that if site *k* is selected and assigned to the central site *l*, i.e., X_{lk} =1, then a CMA centered at site *l* must be formed, i.e. X_{ll} must be 1, otherwise we have

[5] Compactness is not a well defined concept. Note that the absolute value of the compactness measure defined here may not mean much just by itself, rather it has to be considered together with the size of the reserve (number of sites involved). This is because a reserve with only a few distant sites may have a smaller total distance value than a reserve with too many tightly packed sites, whereas in practice the latter should be considered more compact. Although not being fully satisfactory, this definition well serves the specific purposes of the present study. Minimizing the total distance typically results in a circular and connected reserve configuration.
[6] This constraint can also be expressed in terms of a minimum number of parcels or CMA if the effectiveness of conservation effort is related to the reserve size.

X_{lk} =0. We note that the sites that are part of the existing and proposed intensive use military training areas are not eligible for selection, therefore for all such sites we set X_{lk} =0.

The above base model does not incorporate the relocation distances and does not consider the location of individual CMAs relative to other CMAs in the network. We address these issues using a mathematical programming framework and present alternative models to identify the most suitable habitat areas that should be set aside as designated GT habitats.

2.2 Optimal Relocation Model

As mentioned at the outset, over the next few years a significant amount of new land will be utilized as training areas within Ft. Benning. Figure 1 and Figure 2 display the nature of the problem. The current military training areas are shown in Figure 1.a, and the planned intensive training areas to be added are given in Figure 1.b. As can be seen in Figures 1.b and 2.a, the new military training areas contain many GT populations. Therefore those populations have to be moved to new habitat areas that will be selected from among the areas in Figure 2.b that are not planned for additional training uses. The relocation model seeks to select the best CMAs and determine optimal relocation of the existing GT populations that are within the planned new military training areas. The selection of those parcels must be done in such a way that: i) the new protected CMAs must be as compact as possible; ii) each CMA must be large enough to include a sustainable GT population and all CMAs collectively accommodate the GT populations currently located within the planned expansion areas; and iii) the existing populations are moved by minimal distances. The first two criteria are met in the Base Model formulation. The last criterion aims to maximize the survival likelihood of the GT populations that are relocated with the assumption that if the relocation distances are small the GT populations are more likely to adapt to their new environment which would most resemble their original environment[7].

In addition to the notation used earlier we define a new binary variable Y_{lm}, where $Y_{lm} = 1$ if the GT population in site m is moved to the CMA centered at site l. We note that the entire population in a given site is moved together to a new area, i.e. no partial relocation is allowed. We first introduce a Relocation Model which solves the relocation problem without incorporating movement distances and then expand the model to include relocation distances and meta-clustering considerations. The following model, which we call Relocation Model-I, solves the optimal site selection and relocation decisions:

$$\text{Minimize} \quad \sum_l \sum_k X_{lk} * d_{lk}$$

$$\text{s.t.: i)} \quad \sum_l X_{ll} = n$$

$$\text{ii)} \quad \sum_l X_{lk} \le 1 \quad \forall k$$

$$\text{iii)} \quad \sum_k X_{lk} * e_k + \sum_m Y_{lm} * e_m \ge X_{ll} * p \quad \forall l$$

$$\text{iv)} \quad \sum_k X_{lk} * e_k + \sum_m Y_{lm} * e_m \le \sum_k X_{lk} * c_k \quad \forall l$$

$$\text{v)} \quad \sum_l \sum_k X_{lk} * e_k + \sum_l \sum_k Y_{lm} * e_m \ge tp$$

$$\text{vi)} \quad X_{lk} \le X_{ll} \quad \forall l,k$$

$$\text{vii)} \quad Y_{lm} \le X_{ll} \quad \forall l,m$$

$$\text{viii)} \quad \sum_l Y_{lm} = 1 \quad \forall m$$

$$X_{lk}, Y_{lm} = 0,1$$

7 The relocation distances in the model can be replaced with costs attributed with movement. Although relocation (travel) costs were not considered in this application, it can be a significant consideration in many other applications. The model can be easily modified to directly minimize the travel costs by replacing dlk in the objective function with c_{lk}, where c_{lk} is the travel cost between site l and site k.

Several of the constraints given above have already been discussed as components of the Base Model; therefore we describe only the new constraints here. Constraint iv) ensures that for each CMA, the sum of the existing GT population and the new GT populations moved to that area does not exceed the carrying capacity of that CMA, which is the sum of the carrying capacities of individual sites (denoted by c_k) included in that CMA. In this particular application the habitat suitability of each site is represented by an index created from the GT suitability map (Figure 2.b). Constraint vi) states that the GT population in site m can be moved to a CMA with center at l (i.e. $Y_{lm} = 1$) only if such a CMA is indeed formed (i.e. $X_{ll} = 1$), otherwise we must have $Y_{lm} = X_{ll} = 0$. Constraint vii) ensures that the entire population in each new military training site is moved to one and only one CMA. The last constraint was added because GT's are believed to have social interactions; therefore keeping neighboring populations together will reduce the negative impact of relocation.

2.3 Minimum Distance Relocation Model

We extend the above model by adding a movement distance term to the objective function as :

$$\text{Minimize} \quad \sum_{l}\sum_{k} X_{lk} * d_{lk} + \sum_{l}\sum_{m} Y_{lm} * d_{lm}$$

The objective function consists of two parts. The first part is the sum of distances from sites in the selected CMAs to the centers of those CMAs, as in the Relocation Model-I. The second term is the total distance that all GT populations are moved. It may or may not be possible to minimize these two terms at the same time. The extended model, which we call Relocation Model-II, explicitly considers the trade-off between CMA compactness and the relocation distances in a unified framework and determines a compromise solution.

Although this model considers the locations of selected sites relative to the central sites to which they are assigned, it does not consider the location of the CMAs relative to each other or their locations with respect to the surrounding land. Therefore, the model is indifferent between two CMA configurations where one CMA network includes closely placed multiple CMAs while the other includes remote CMAs as long as the specified conservation targets are satisfied and the movement distances are minimized. Incorporating such aspects may have significant impact on site selection decisions. These issues are addressed in the modified meta-clustering formulations below.

2.4 Meta-Clustering

The purpose of this model is to extend the Base Model to incorporate distances between multiple CMAs so that not only are the sites in each CMA compact but also the CMAs themselves are close to each other. We first define the distance between two CMAs as the distance between their centers. Inter-habitat distances can be incorporated in different forms. Here we present two formulations; first we introduce Meta-Clustering Model I, a model that places an absolute distance criterion on meta-clustering by adding an additional constraint; second we present Meta-Clustering Model II, a multi-objective approach that uses a new variable to identify a meta-center and incorporates distances from individual CMA centers to the meta-cluster center.

In the first approach described below the objective function remains unchanged from the Relocation Model-I. An additional constraint restricts the distance between each pair of CMAs to a specified maximum distance, denoted by $\bar{d}$. Thus, this approach groups CMAs together and leads to a compact constellation of CMAs if $\bar{d}$ is chosen sufficiently small[8]. The new constraint is described below:

ix) $d_{lk} * (X_{ll} + X_{kk} - 1) \leq \bar{d}$ for all $l \neq k$

To explain how the constraint works, consider the case $X_{ll} = X_{kk} = 1$ for some pair of sites *l* and *k*, which means that two CMAs are centered at those sites. Then, we must have $d_{lk} \leq \bar{d}$, i.e., the central sites of those CMAs cannot be far from each other more than $\bar{d}$. For all other combinations of X_{ll} and X_{kk}, i.e. $(X_{ll}, X_{kk}) = (1,0), (0,1), \text{and } (0,0)$, the constraint becomes redundant. Therefore, only those sites that are closer to each other than $\bar{d}$ qualify as CMA centers and the model selects the best ones in light of cluster compactness and habitat suitability[9].

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[8] An alternative approach to the problem is to apply the method used in the Base Model for clustering the cluster centers, namely we may determine a 'universal center' for the entire reserve system, which may be any site or required to be a cluster center itself) and minimize the sum of distances from the cluster centers to that site along with the sum of distances from individual sites to their assigned cluster centers. This approach requires substantially more variables and constraints in addition to the ones involved in the Base Model. In order to identify the universal center and compute the distances from all cluster centers to that site we introduce a binary variable Y_{lm} where Y_{lm}=1 if parcels *l* is the universal center and *m* is a cluster center of a reserve, otherwise Y_{lm}=0. The requirement of one central site for the entire reserve system is ensured by the constraint: $\sum_l Y_{ll} = 1$, and the assignment of cluster centers to the universal center is governed by $Y_{lm} \leq Y_{ll}$ for all l, m. Finally, the *Y* variables are related to previously defined *X* variables through the constraints $Y_{lm} \leq X_{ll}$ and $Y_{lm} \leq X_{mm}$ for all l, m, which imply that in order to have Y_{lm}=1 we must have $X_{ll} = X_{mm} = 1$, namely there must be two clusters centered at sites *l* and *m*, respectively. Minimization of $\sum_{l,k} d_{lk} * X_{lk} + \sum_{l,m} d_{lm} * Y_{lm}$ tends to select clusters as closely as possible. The first term in the objective function is the sum of distances from all selected parcels to their respective cluster centers, while the second term is the sum of distances between cluster centers to the universal cluster center. If the total distance between cluster centers is relatively small compared to the sum of total distances between selected sites and their cluster centers, one may consider a weighted average of the two total distance terms where the weights are positive scalars and represent the importance of the two attributes (i.e, compactness of the entire reserve vs. compactness of individual reserves).

[9] Reversing the direction of the inequality in the last constraint spreads clusters in the area and moves them away from each other by a distance exceeding $\bar{d}$, which aims to reduce the likelihood that the entire reserve system can be affected by an outbreak of diseases.

For the second meta-clustering approach, in addition to the notation used earlier we define two new binary variables[10] Z_{lk} and D_l, where $Z_{lk} = 1$ if site l represents the meta-center and a CMA centered at k is assigned to the meta-center at l; and $D_l = 1$ if parcel l serves as the meta-center. The objective function in the Relocation Model-I is modified by including a term that incorporates the distances from the meta-center to the centers of the selected CMAs. The updated objective function takes the form:

$$\text{Minimize} \quad \sum_l \sum_k X_{lk} * d_{lk} + \delta \sum_l \sum_k Z_{lk} * d_{lk}$$

where the new second term is the sum of distances between selected CMAs' centers and the meta-center and $\delta > 0$ is the relative weight assigned for the meta-clustering objective (or a penalty parameter which promotes the minimization of the total inter-CMA distances, thus improved clustering. Therefore the model explicitly considers the trade-off between CMA compactness and meta-clustering of the CMAs and determines a compromise solution. The following three additional constraints are introduced to govern the selection of the meta-cluster.

ix) $$\sum_l D_l = 1$$

x) $$\sum_k Z_{lk} \le m * D_l \quad \forall l$$

xi) $$\sum_l Z_{lk} \ge X_{kk} \quad \forall k$$

$$D_l, X_{lk}, Z_{lk} = 0,1 \quad \forall l,k$$

[10] Binary variables extend the size of the branch and bound tree, which typically leads to a longer computation time. Instead of L^2 new binary Z_{lk} variables we may define Z_{lk} as a positive variable and use 2L binary D variables to ensure that Z_{lk} takes binary values as

ix) $\sum_l D_l = 1$

x) $\sum_k Z_{lk} \le m * D_l \quad \forall l$

xi) $Z_{lk} \ge D_l + X_{kk} - 1 \quad \forall l,k$

$D_l, X_{kk} = 0,1 \quad \forall l,k \quad Z_{lk} \ge 0 \quad \forall l,k$

Constraint ix) ensures that there is only one site selected as the meta-cluster center. Constraint x) ensures that if some site k is assigned to the meta-center centered at l, in which case we have $\sum_{k} Z_{lk} \geq 1$, then $D_l = 1$, that is site l has to be the meta center. Constraint xi) ensures that if k is a habitat center, $X_{kk} = 1$, then it is must be assigned to the meta-center l and the distance between sites l and k is accounted for in the objective function.

3. Data

The current and future military training areas were obtained as raster files from Ft. Benning and are shown in Figure 1.a and 1.b. The habitat areas suitable for GT were obtained as raster files from the national biological information infrastructure [29]. The above raster files were converted to ESRI shape files using ARC GIS 9.2. The resulting shape file is shown in Figure 2.b. A 40x40 grid file, where each grid was 900m by 900m, was created using Geoda and the grid shape file was spatially joined with the above shape files using spatial join tool in ARC GIS. The spatial join gives the grid file the attributes of the shape file. To ensure that each grid cell represents a density of the original data, the “sum” option was used when joining the GT burrow data and the habitat suitability data.

The grid cell values for figure 1 are specified as binary values (grid cell value = 1 if cell includes a base area or a planned expansion area). The grid cell values for figure 2 are given as an index. For figure 2.a, each grid cell value is the sum of the number of observed GT burrows within the grid cell, the index ranging from 0 to 350. For figure 2.b, the grid cell value is the sum of the suitable points (the GT suitability raster map was converted to point shape file) within the grid cell. The suitability index ranges from 0 to 864. The GT population density parameter δ is used with this grid cell value to reflect the sustainable number of GT's for each CMA. The population density is introduced into the model by multiplying population of GT in site k, e_k, by δ. A one-hectare land parcel can support between 2 to 4 GT's. This is equivalent to supporting between 180–360 GT per site at the 900m x 900m resolution. Therefore the density parameter is set to 0.5 for the empirical analysis.

4. Empirical Results and Discussion

This section presents the results of the Relocation Model-I, Relocation Model-II, and the two meta-clustering models. All models were solved using GAMS/CPLEX version 21.6 on a PC with an Intel Core 2 Duo processor and 2 GB of RAM running Windows XP.

The total population of GT that may need to be relocated is estimated to be at least 1800. This is based on the actual burrow counts in the areas that will be allocated exclusively to military uses (see Figure 1.b). Because there are existing GT populations in the potential CMAs we needed to consider an overestimate of this figure when restricting the minimum population size that the entire conservation area should hold after relocation (i.e. the parameter tp in constraint *iv)* of Model-4). Here we assumed that the final total population in all CMAs (including the existing GT populations and the relocated populations) is at least 4000. In theory, the GT populations that are currently located in the planned military expansion areas can be moved to a single large CMA or multiple smaller CMAs (all located outside the area that will be required for intensive military use). We require the CMAs to be as compact as possible and assume that sites belonging to the intensive-use maneuver zones are not eligible for selection. The model is solved with various parameter specifications for the number of CMAs (n). The reasons for specifying more than one CMA are three-fold. First, we may want to separate the relocated GT population into smaller populations, each being located in a different part of the CMA, to safeguard them against potential diseases that may occur in on a protected area and spread to the other areas. Second, one big CMA requires movement over large distances of several populations located in different parts of the new training zones, which might create a more challenging adjustment problem particularly for the populations relocated to distant areas. Third, setting aside one large conservation area reduces the flexibility for the military when further expansion of training areas is needed in future. These problems can be alleviated or reduced by designing multiple small conservation areas.

In all of the runs described below the minimum population for each CMA was specified as 750 and the minimum total population was specified as 4000. The Relocation Model-I and Relocation Model-II were solved with one, two, three and four CMAs. The two meta-clustering models were solved each with four CMAs. These numbers are specified arbitrarily to illustrate the workings of the models and demonstrate the trade-offs between different spatial criteria.

4.1 Base Relocation Results

The Relocation Model I results, without spatial considerations other than compactness of the selected CMAs are shown in Figure 3 for 1, 2, 3 and 4 CMAs. Comparing the results in Figure 3 with the suitability map given in Figure 2.c illustrates that the Base Model simply selects from amongst the most densely packed and best available sites to form contiguous and compact CMAs. The optimal solution with one large conservation area (Figure 3.a) shows that this area would be located at the southeast corner of the installation. However, the compactness of the

CMA is poor; the selected sites (16 total) are meandering in shape. This result is driven primarily by the fact that the model is forced to choose one cluster of habitat sites and the only available good quality sites that are not currently populated heavily by GT are in that part of the installation. The good quality sites in other parts of the installation are not in the solution due to three reasons: i) those sites are under extensive military use, ii) a high density of GT currently inhabiting the sites would not allow relocating new GT's into those areas, or iii) those sites are located far apart from each other.

For the two-CMA case the model chooses two clusters with four and eight sites, respectively (Figure 3.b). The three-CMA case selects a total of ten sites (Figure 3.c), and the four-CMA case requires a total number of 11 selected sites (Figure 3.d). Unlike the one big CMA scenario, the two, three and four-CMA configurations comprise of compact clusters of sites since instersite distances are accounted for each cluster separately, rather than the distances between all selected sites, which allows the model to choose closely located sites from multiple locations. Based on these results, we may conclude that if the size of the total area to be CMAs is a concern, forming three CMAs, two located in the southwest and one located in the north-central areas, would be the best strategy as it involves the minimum number of sites (=10).

4.2 Minimum Relocation Distance Results

The results of the minimum relocation distance model are shown in Figure 4. The optimal solution with one large conservation area (Figure 4.a) shows that this area would again be located at the southeast corner of the installation (although slightly different from the solution displayed in Figure 3). The compactness of this CMA is even poorer, where among the 16 selected sites one site is disjoint from the other sites. Besides the reasons that were discussed above, minimizing the relocation distances as an additional consideration works against the primary objective (i.e., compactness) when only one cluster is being selected.

The results for two CMAs are shown in Figure 4.b. The change in the CMA locations is dramatic when compared to Figure 3.b. Incorporating the relocation distances in the objective function (besides compactness) moves the selected clusters towards the top center and bottom center of the installation. None of the southeastern sites was chosen; instead 8 sites in the north and 11 sites in the south are selected to form the two CMAs. Compared to Figure 4.a, the factors behind this selection are: i) minimizing the movement distances makes the sites in the those two locations more attractive than before because they are closer to the current GT habitats; ii) the smaller population size requirement for individual CMAs allows selecting smaller CMAs with better habitat quality, which was not possible in the previous case (Figure 4.a).

The results for three and four conservation clusters are shown in Figure 4.c and Figure 4.d. Once again a dramatic change occurs in the CMA configuration compared to the results in Figure 3.c and Figure 3.d. For the three-CMA scenario, the model chooses 17 sites which are centrally located and relatively close to the area where GT's are to be relocated from. The model does not choose any site from the highly suitable south-east corner, since the movement distances to those sites are higher. For the four-CMAs, scenario, the model chooses a total of 16 sites, again among the centrally located sites. The four sites in the southeast (best ones from the solution with one large CMA cluster) form a CMA in that area, which is much smaller than the first solution however, while three small CMAs are formed in the northeast, central and southern parts of the installation. This result is driven again by the habitat quality and relaxed CMA size limitation as well as the preferred compactness property and the aim to reduce the total relocation distance. A clear distinction between the CMAs seen in Figure 4 and the ones in Figure 3 is that the four CMAs found without consideration of relocation distances are much more compact. This is an intuitive and expected result, indicating the trade-offs between competing objectives, namely relocation distances and compactness of individual CMAs. Another evident distinction between the two sets of CMA configurations in Figures 3 and 4 is that the relocation model selects larger clusters of sites compared to the model that considers compactness only. This result is driven jointly by the relocation distances and habitat qualities of individual sites. More specifically, consideration of relocation distances favors the sites that are closer to the current GT habitats, which are (in this data set) of poorer quality than the remote but good quality sites shown in Figure 3. It should be noted that the weights assigned to the CMA compactness and total distance of relocation objectives heavily influence the outcomes. Assigning a higher weight to compactness results in more compact and usually contiguous, CMA configurations; on the other hand, placing a higher weight to the relocation distance shifts the CMA locations towards the planned military training areas, which typically reduces the compactness of individual CMAs.

4.3 Meta-clustering of Multiple CMAs

The results of the Meta-Clustering Model I are shown in Figure 5. To highlight the role of meta-clustering, only the results for four CMAs and four different inter-CMA maximum distance specifications ($\bar{d}$) are presented. We measure the distance between any two CMAs by the Euclidean distance between central sites of those CMAs. The four distance specifications we considered in the applications whose results are shown in Figure 5 were $\bar{d}$ equals (a) 30 cells (27 km), (b) 25 cells (22.5 km), (c) 20 cells (18 km), and (d) 15 cells (13.5 km).

The results for a maximum inter-cluster distance of 30 cells are presented in Figure 5.a. The results are identical to the base case results for four CMAs implying that the maximum distance constraint is not actually binding. Decreasing the maximum distance specification alters the meta–clustering solutions as displayed in Figure 5.b-d. For instance, reducing the maximum inter-cluster distance from 30 to 25 cells (Figure 5.b) moves the southwest cluster to the southeast, a region that has a large aggregation of suitable sites. In both cases a total of 11 sites are selected for the four CMAs, but the selected CMAs are much closer to each other (compare Fig. 5.b with Fig. 5.a). Figure 5.c displays the results for a maximum inter-cluster distance of 20 cells. Two of the southwest CMAs are now moved the northeast area, because of the availability of equally suitable sites in that area within close proximity to each other. Figure 5.d displays the results for a maximum inter-cluster distance of 15 cells. This forced the selected CMAs to be tightly packed, where all four clusters are located in the southeast area and are adjacent to each other forming a big large CMA similar to the base case solution with one cluster.

As the maximum inter-cluster distance is reduced, the set of suitable and available sites decreases, forcing the model to choose a larger number of less suitable sites at the cost of compactness. In Figures 5.a and 5.b a total of 11 sites are selected in each case, whereas in Figure 5.c, 13 sites are selected, which increases further to 14 sites in Figure 5.d.

Figure 6 displays the results of the Meta-clustering Model II where clustering is achieved by penalizing the dispersion of CMAs in the objective function. Again, to highlight the model's performance we present only the results for four CMAs and four meta-clustering weights (σ), specifically σ = 0.00, 0.06, 0.09 and 0.10. The results for σ =0 are presented in Figure 6.a. As could be expected, the results are identical to the base case results for four CMAs. The results for σ =0.06 are presented in Figure 6.b. The selected clusters are located closer together and the maximum inter-cluster distance is reduced compared to the configuration in Figure 6.a. Increasing the weight to 0.09 (Figure 6.c) puts three of the four CMAs together in the southeast, with only one CMA being located farther away. This last CMA is needed because forming a sufficiently small and compact CMA from the unselected sites in the southeast (to decrease the total inter-CMA distance) was not possible while providing a sufficient carrying capacity to include all the GT's that are accommodated by the CMA in the southwest. As the weight is increased to 0.1, the inter-site distances have a bigger impact on the objective function; therefore as can be seen in Figure 6.d, the model selects four clusters that are adjacent to each other. As expected this results is similar to the one cluster base case and identical to the constraint meta-clustering model with a short inter-cluster distance (see Figure 5.d). Compared to the selection in Figure 6.c, the model now selects two additional sites (12 sites in 6.c versus 14 sites in 6.d). Although this increases the total inter-site distance value (the first summation in the objective function), the higher weight used for meta-clustering counterbalances that adverse effect. The model results with the two meta-clustering formulations are quite sensitive to the specification of the objective function weight σ and constraint parameter $\overline{d}$, therefore it would be ideal to use the proposed methods in close collaboration with the land managers.

5. Concluding Remarks

This paper presents several linear integer programming formulations that can be used to incorporate relocation distances and meta-clustering as spatial criteria in designing conservation management areas (CMA)s. We apply the models to a real data set pertaining to a military installation where protection of Gopher Tortoise, a key stone species at risk, is of concern. Though the models are complex and the empirical applications demonstrate that they are computationally convenient (can be solved within a reasonable computation time, at least for the data set used here). The results of the models are consistent with intuition and reflected the desired outcomes; the meta-clustering model selects CMAs that are clustered (in close proximity to each other) and the individual CMAs are compact. It should be noted that adding the spatial requirements can require the model to select from among less suitable parcels when the best parcels did not meet the specified spatial criteria. This in general leads to the selection of larger CMAs, poorer compactness of some CMAs, or reduced meta clustering of multiple CMAs. Therefore, there is a trade-off between spatial considerations and economic efficiency in optimal selection of conservation CMAs.

The grid cells (sites) considered as decision units in this study are rather large (900mx900m). In many practical CMA design problems much smaller areas may have to be considered as decision units, depending on various factors such as data accuracy, site costs, and uniformity of each site in terms of habitat characteristics. This may increase the model size considerably and computational difficulties may arise. For conservation analyses that require higher resolution, it is possible to conduct a multi-step modeling approach, where low resolution data is used to locate the general area and successively higher resolution data is used for the surrounding area in successive model runs. In each successive run the model may be restricted to the area selected in the previous run and the large grid units in that selection can be divided into sufficiently small spatial decision units to identify the specific conservation areas at desired resolution.

According to the relocation model results, it is possible to form up to four centrally placed CMAs within the new military areas that are in close proximity to the original GT habitat areas. The CMAs become smaller and more compact, and comprise higher quality sites as the allowed number of CMAs is increased. However, they may be dispersed throughout the installation area. When a clustering objective (meta-spatial consideration) is imposed on site selection, a few more CMA sites were selected and the CMAs were located in areas containing less suitable sites. These results provide general guidelines and will be useful for on the ground decision makers. Perhaps the most important empirical finding of this study is that regardless of the spatial considerations imposed in each case, the GT habitat conservation objective can be served by designating a little amount of land, thus without significant sacrifice in the use of the military area for training purposes.

Finally, it should be noted that this paper is more than an empirical analysis of GT conservation in a military area. By successfully incorporating ecological and spatial consideration into linear site selection models, we illustrate that it is possible to generate optimally designed conservation CMA configurations using integer programming. With appropriate modifications the methods introduced here are applicable to many other conservation problems involving endangered and at-risk species and can be extended to include multiple species and multiple land uses. These methods can also be applicable to many other problems of land use/allocation, such as optimal selection of nature CMAs, districting, or optimal urban expansion. For instance, determining optimal locations of open spaces (nature reserves) in and around urban areas has much similarity to the relocation problem addressed here.[11] Therefore, we view the methodological aspects of the paper as equally valuable as its empirical findings for the particular problems we dealt with.

[11] The importance of movement distances may be seen as overemphasized in the GT relocation problem (as relocation is to occur only once, thus the cost involved would be little), but the distances between 'origins' (urban areas) and 'destinations' (open spaces) may be of serious concern in the nature reserve design problem where it is desirable to locate nature reserves as close as possible to urban areas (to serve as open spaces). The excessive cost of numerous repeated trips by numerous people between the urban areas and open spaces over a long time horizon would be substantial even if the total distance is slightly suboptimal.

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7. References

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8. Figure Captions

Figure 1: Land use and GT habitat suitability in Ft. Benning. a) Locations with current intensive military use; b) Proposed areas for additional intensive military use; c) Location of highways and major paved roads

Figure 2: a) Location of observed GT habitats (based on burrow counts); b) Location of suitable GT habitat areas, c) Quality of suitable habitat areas (darker shade indicates higher quality)

Figure 3: Relocation Model I; solutions for compact reserve configurations with (a) one reserve; (b) two reserves; (c) three reserves; (d) four reserves. The lighter shaded areas indicate the current (blue) and proposed (red) military training areas, while the darker shaded areas (shown with the parcels included) indicate the conservation sites chosen by the model. Black circles are used to identify the selected reserves.

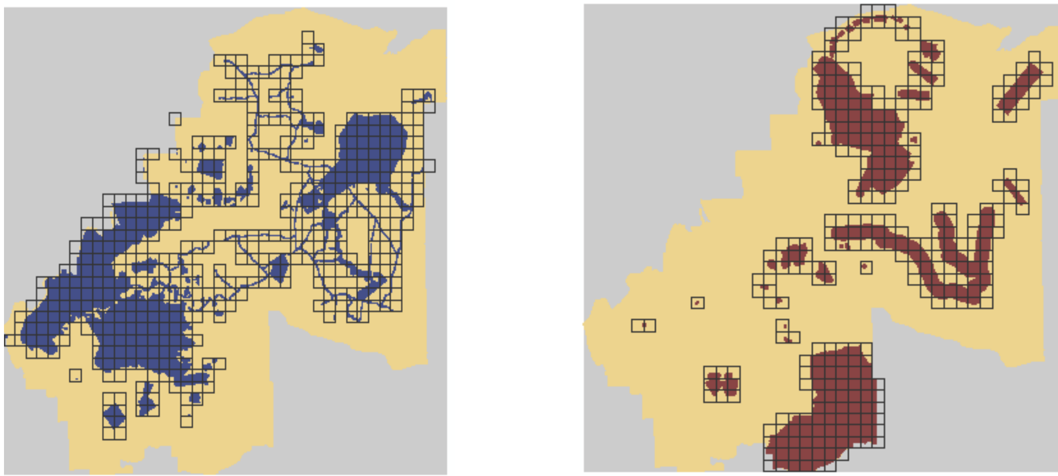
Figure 4: Relocation Model II; solutions for compact reserve configurations that minimizes movement distances with (a) one reserve; (b) two reserves; (c) three reserves; (d) four reserves. The lighter shaded areas indicate the current (blue) and proposed (red) military training areas, while the darker shaded areas (shown with the parcels included) indicate the conservation sites chosen by the model. Black circles are used to identify the selected reserves.

Figure 5: Meta-Clustering Model I; solutions for compact reserve configurations with constraint meta-clustering for four reserves with a maximum inter-site distance of (a) 30 cells (27 km); (b) 25 cells (22.5 km); (c) 20 cells (18 km); (d) 15 cells (13.5 km). The lighter shaded areas indicate

the current (blue) and proposed (red) military training areas, while the darker shaded areas (shown with the parcels included) indicate the conservation sites chosen by the model. Black circles are used to identify the selected reserves.

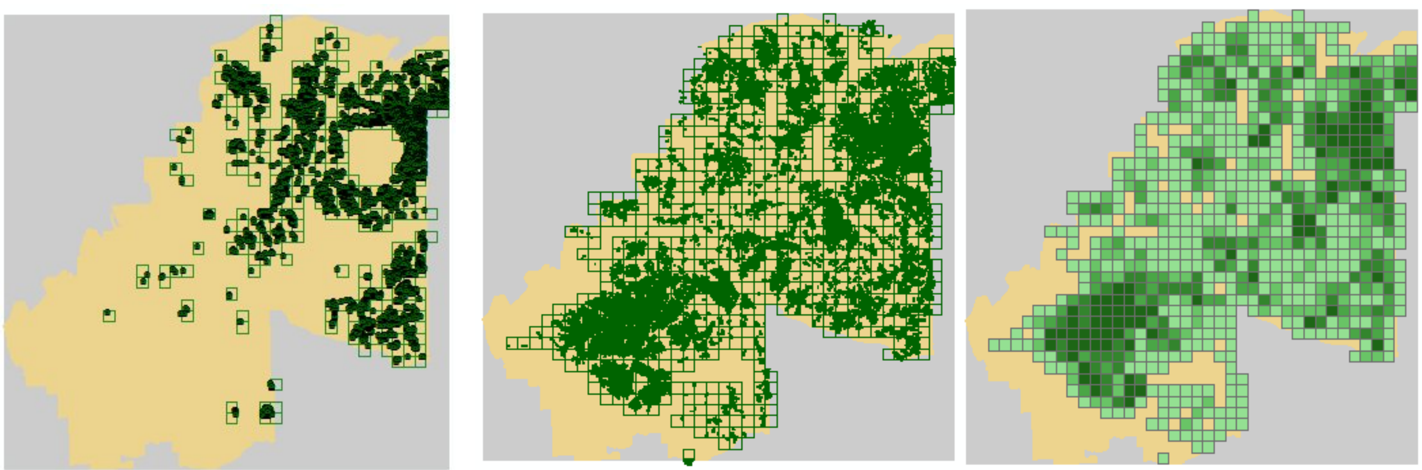
Figure 6: Meta-Clustering Model II; solutions for compact reserve configurations with constraint meta-clustering for four reserves with a meta-clustering weight of (a) 0.00; (b) 0.06; (c) 0.09; (d) 0.10. The lighter shaded areas indicate the current (blue) and proposed (red) military training areas, while the darker shaded areas (shown with the parcels included) indicate the conservation sites chosen by the model. Black circles are used to identify the selected reserves.

9. Figures (we will provide both color and gray scale images at the desired resolution for print and online publication)



(a) (b)

Fig 1 – Locations of current and future intensive military use



(a) (b) (c)

Fig 2 - Location of observed GT habitats

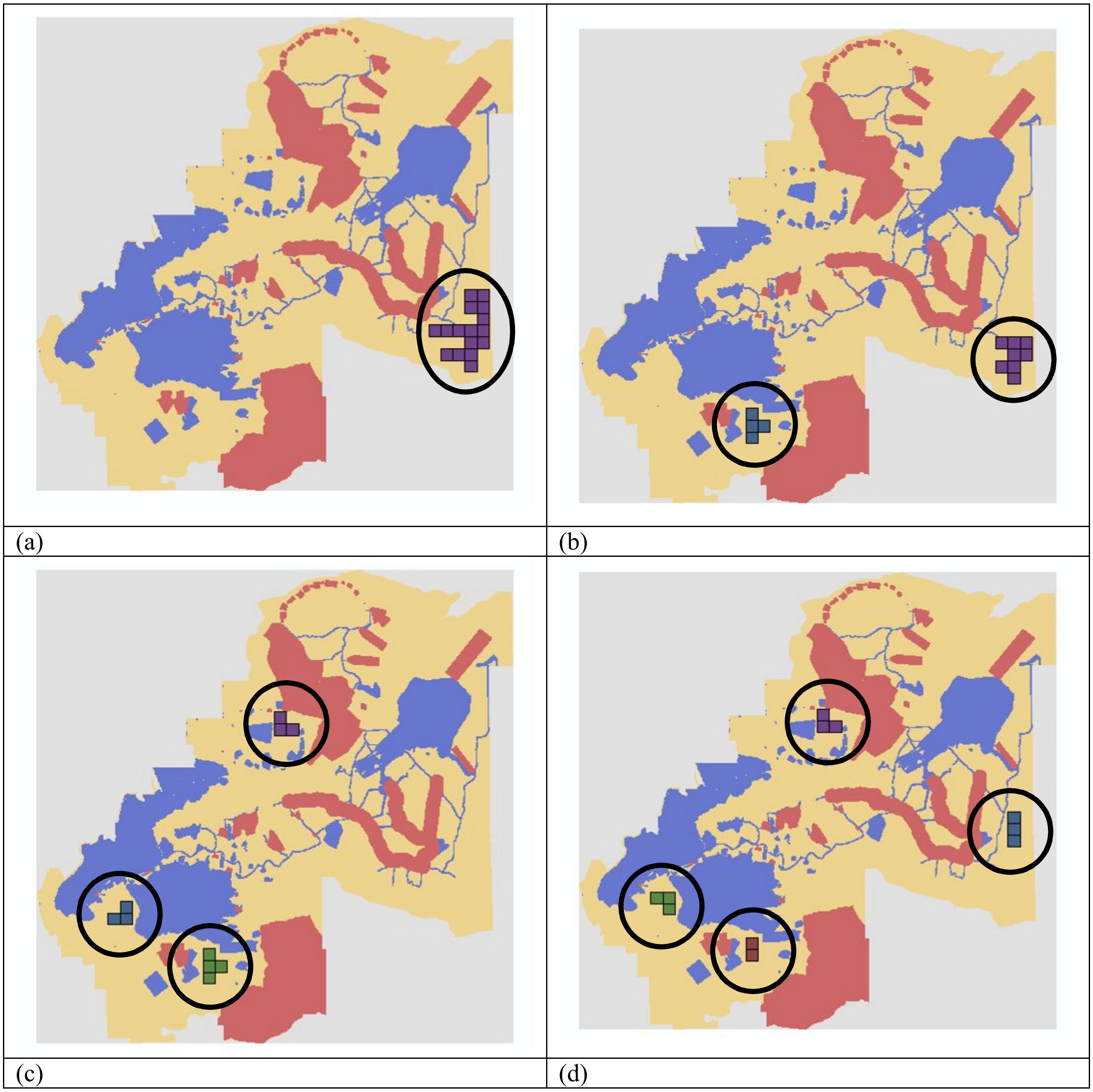


Fig. 3 – Relocation Model I Results

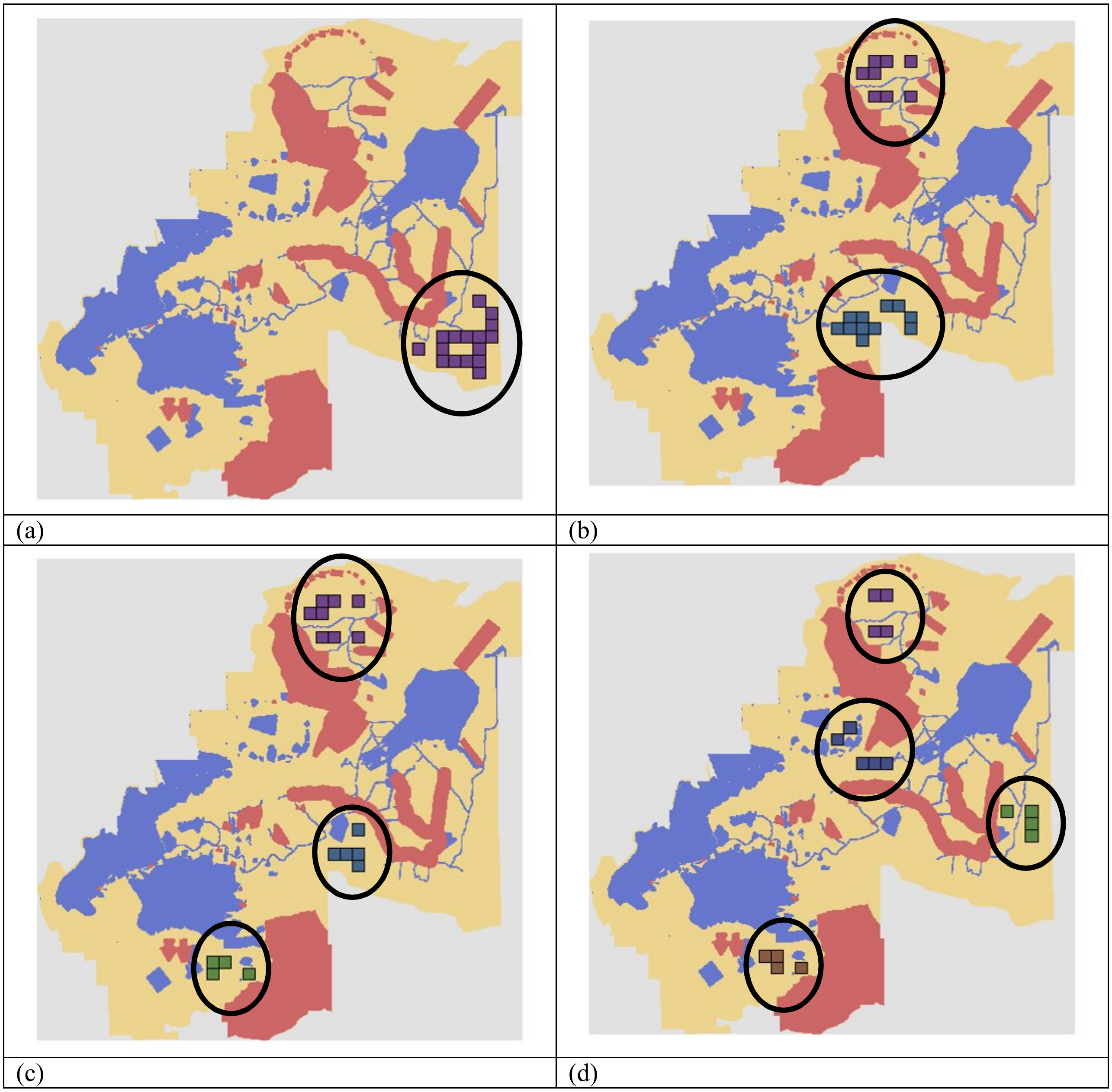
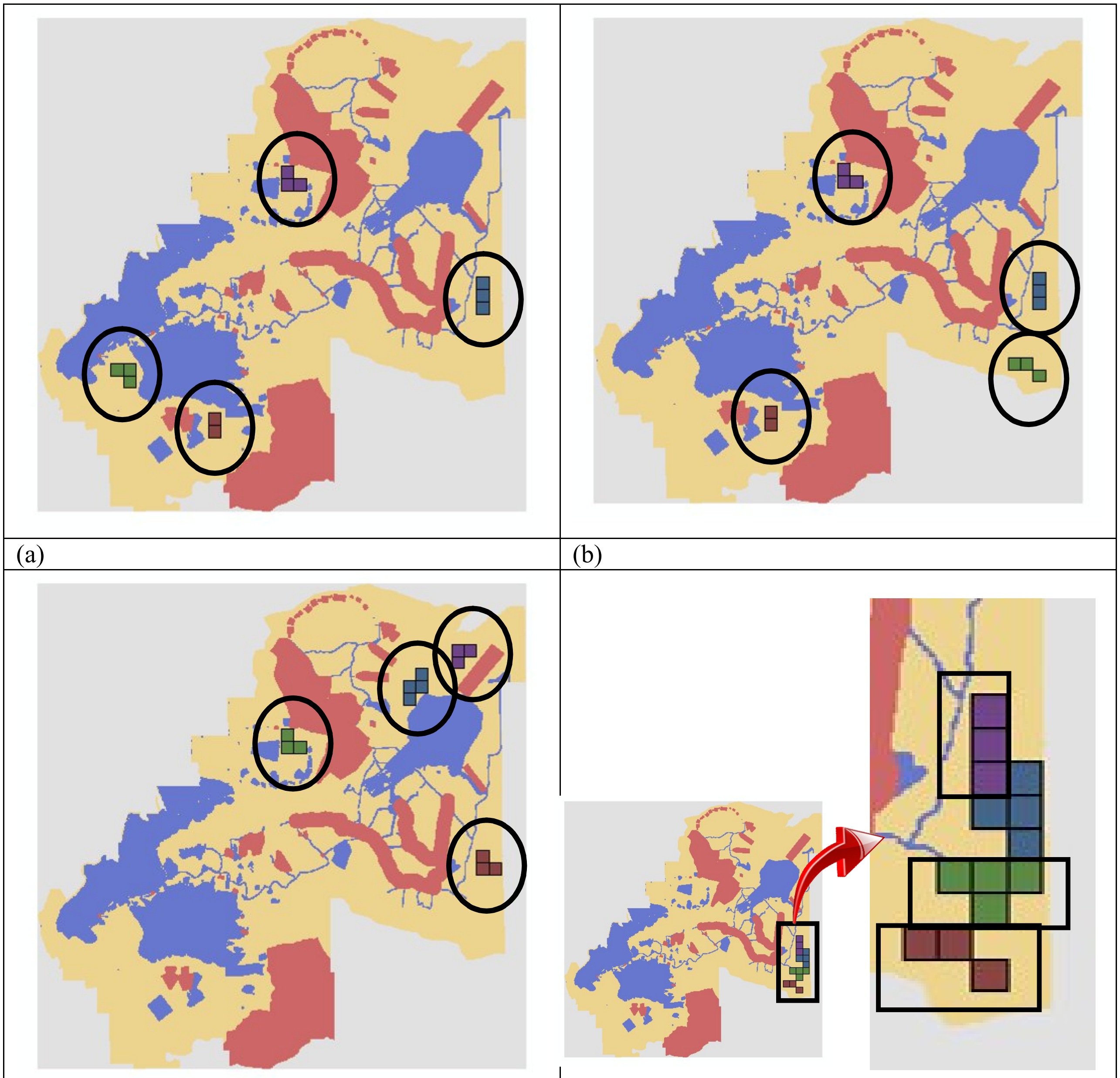

(a) (b) (c) (d)

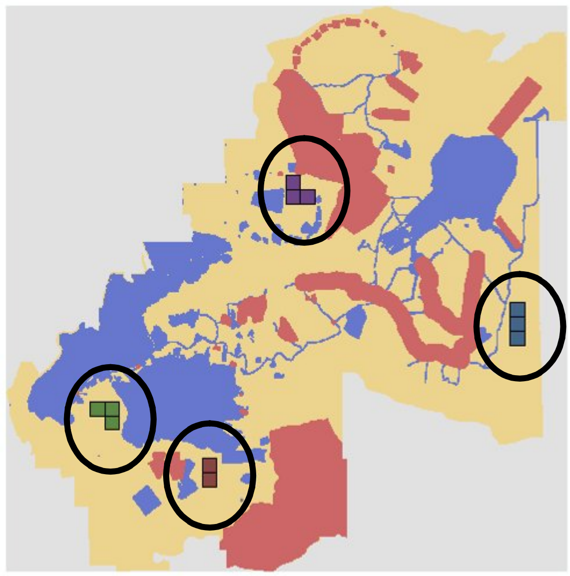
Fig. 4 – Relocation Model II Results



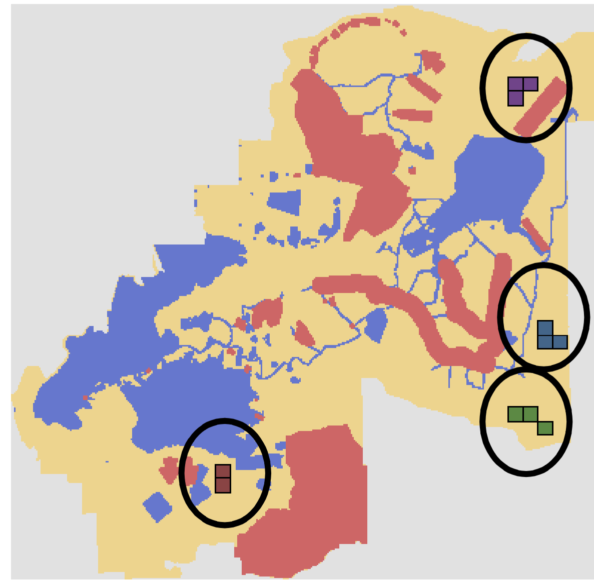
(a) (b)

-(c) (d)

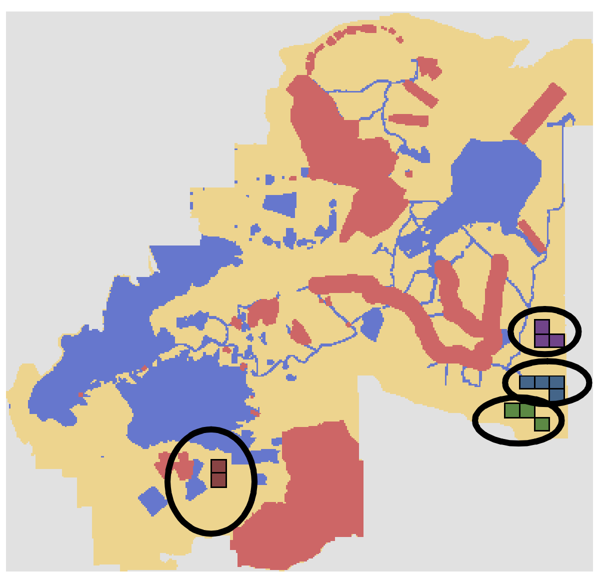
Fig. 5 – Meta-clustering Model I Results



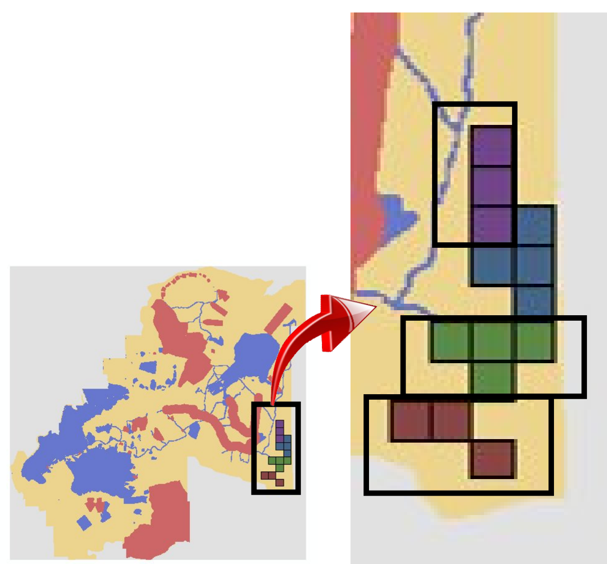
(a)



(b)



-(c)



(d)

Fig. 6 – Meta-clustering Model II Results