

Comparative Abilities of Vegetation and Ground Cover Methodologies to Predict the Locations of Two Chipmunk Species in the Sierra Nevada Mountains

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ABSTRACT

Climate change is a problem of global significance, but the severity of the threat varies spatially. Climate models predict higher than average temperature increases in most alpine areas. Biotic responses to climate change are still being researched, but one well-documented mechanism is an elevational range shift, where a plant or animal species migrates upslope to escape warming temperatures. The Grinnell Resurvey Project documents elevational range shifts in the California Sierra Nevadas. Two sympatric chipmunk species (*Tamias alpinus* and *Tamias speciosus*) have exhibited range shifts in Yosemite National Park and environs. Over the past 100 years, *T. alpinus* has undergone an upward contraction in its range. *Tamias speciosus* has expanded its range both upward and downward over the same time period. These disparate responses are of particular interest due to the two species' similarity. To understand the role of habitat selection in this process, I compared methodologies of vegetation surveys. To assess the efficacy of data at various spatial scales, I built models predicting chipmunk presence using remote sensing (RS) and field survey data. Bedrock was the strongest predictor of *T. alpinus* presence (2013: $p = 2.361 \times 10^{-8}$; 2014: $p < 2.2 \times 10^{-16}$). Litter/duff was the strongest predictor of *T. speciosus* presence ($p = 6.14 \times 10^{-10}$). Results show that field survey models are generally better than RS, though mixed models of both RS and field survey variables perform about as well. Future development of mixed models allows researchers to complete vegetation surveys more efficiently and devote more field research to their species of interest.

KEYWORDS

range shift, remote sensing, vegetation survey, *Tamias*, climate change

INTRODUCTION

As global change progresses and environments around the world undergo modification, it becomes increasingly critical to understand why species live where they do. Knowledge of vegetation and abiotic habitat patterns are important to understanding the biology, ecology and conservation of species in the context of changing environments (Tammone et al. 2012). Climate change in particular has caused the ranges of many animal species to shift upwards in latitude and elevation, presumably to track the cooler temperatures that exist at higher latitudes and elevations, or to track shifting food sources (Parmesan 2006).

This phenomenon of range shifting has been recorded in ecological preserves such as national parks, adding further support for the role of broad-scale climate changes, rather than localized human impacts, in inducing shifts (Monahan 2014). The legal designation of parks as environmentally protected areas does not make them immune from the effects of climate change; in the U.S., national parks are experiencing extreme historical high temperatures, across several variables (Monahan 2014). One significant study of range shifts in protected areas comes from the Grinnell Resurvey Project (GRP). In this project, UC Berkeley scientists researched an elevational transect in Yosemite National Park and its environs, focusing on quantifying the impacts of climate change. Researchers resurveyed an elevational transect (60 to 3300m above sea level) originally sampled by Joseph Grinnell between 1914 and 1920 and estimated historical and current detectability of several terrestrial vertebrate species using daily trapping records. As a result, they were able to document long-term biogeographic responses to climate change (Moritz et al. 2008). Although many species did shift upwards in elevation as expected, many expanded or did not shift; there was large heterogeneity in response.

The alpine (*Tamias alpinus*) and lodgepole chipmunks (*Tamias speciosus*) in Yosemite National Park, CA, demonstrate this heterogeneity in response. GRP results showed that in this area *T. alpinus* has contracted its range upwards at the lower limit by 629 meters since 1919. The co-occurring *T. speciosus* has not significantly shifted its range over the same time period (Moritz et al. 2008). Reasons for these disparate responses are unclear; however, habitat preferences have been shown to differ between the two species (Rubidge 2010). *Tamias alpinus* tends to live above the tree line, in rocky areas such as boulder fields, alpine meadows and scree slopes (Clawson 1994). *Tamias speciosus* inhabits forested areas with large boulders and some open ground (Best

1994, Waters and Zabel 1998). In general, whether these species are tracking physiological niches or diet sources is still a question, though certain well-studied systems suggest that both are a possibility (Chappell 1978, Heller and Gates 1971).

Tamias alpinus and *T. speciosus* have become an important focal system for understanding why there is such heterogeneity in biotic responses to climate change, even among closely related co-occurring species. Current work explores genetic (e.g. Rubidge et al. 2012, Bi et al. 2013), morphological (Assis, unpublished data), diet shifts (Walsh, not yet published), and physiological differences (Hammond 2015) in these species. Because of this focus, it is important to understand more about the species' basic biological history, including habitat preferences. Consequently, this project will explore habitat differences between these two species.

Various methods exist for assessing the chipmunks' habitats. GRP researchers have conducted a variety of field vegetation surveys at trapping locations throughout Yosemite National Park and surrounding areas. These methods were adapted from the California Native Plant Society's Vegetation Rapid Assessment Protocol (DFS 2007). Field surveys can provide very fine-scaled data, but they can be time-consuming. Digital data can be produced efficiently and used for a wide variety of purposes; however, the resolution is not as fine-scaled as field surveys. Geographic Information System (GIS) data can help researchers better understand biogeographic questions by analyzing the spatial patterns of ecological processes (Skidmore et al. 2011). Over the past 30 years, GIS tools, which integrate huge amounts of geo-referenced data such as elevation, climate, slope, and vegetation patterns, have been used to assess ecological patterns at a variety of spatial scales; to solve basic research questions; to test scenarios of environmental policies and monitoring goals; and for many other purposes (Skidmore et al. 2011). Increasingly, GIS research incorporates remotely sensed (RS) data, which refers to information collected about the Earth's surface without coming into physical contact with the surface (in contrast to field measurements). Typically, RS takes the form of overhead or satellite imagery, with reflectance information recorded in various bands of the electromagnetic spectrum. RS data can be used to answer biogeographic questions by allowing for easier modeling of species' habitats and vegetation communities at large spatial scales (Skidmore et al. 2011).

GIS and RS data range from global to hyperlocal (<1m) in scale, and the resolution required will depend on the specific research questions of interest (Skidmore et al. 2011, Scherrer and Körner 2010). For example, maps depicting global climate change models might rely on global

temperature data, while municipal land use maps require precision of <1m. Although advances in RS technology, including the proliferation of research drones, have led to improved ability to acquire high-resolution imagery of remote areas, such information gathering can be prohibitively expensive. As a result, on-the-ground field surveys are still frequently implemented to collect high-resolution field data that can complement RS/GIS data. For instance, public digital vegetation data for the state of California is assessed using both remote sensing and ground based sampling techniques (Warbington et al. 2000). It is unclear how the results of digital and field-based vegetation and habitat surveys compare (Tammone et al. 2012).

Understanding a region's vegetation can allow for the generation of better predictive habitat models, which can aid in conservation and management (Guisan and Zimmermann 2000). The objective of this project is to compare methods of collecting data on these species' habitat preferences. Specifically, I compared the accuracy with which field-collected and remotely-sensed vegetation data predict the trapping locations of *T. alpinus* and *T. speciosus*. I quantified and compared the results of different kinds of vegetation surveys in predicting the presence of each species. I also delineated the vegetation and habitat preferences of the two chipmunk species, based on the literature and field data. Finally, I analyzed the vegetation data to assess which qualities are the best predictors of chipmunk trapping success and to determine which survey method best represents those qualities.

METHODS

Study species

Of the two species, *T. alpinus* is the smaller (~30-50g), and its range extends higher in elevation. Its diet chiefly comprises the seeds of sedges and other alpine plants (Best 1994). *Tamias speciosus* is slightly larger (50-80g) and has a more generalized diet, consisting of seeds, fruits, berries, insects, and picnic scraps (Clawson 1994). *Tamias alpinus* now occurs at elevations from 2936 to 3353 meters, while *T. speciosus* occurs at 1896 to 3220 meters (Moritz

et al., 2008). *Tamias speciosus* is found at tree line but rarely above, while *T. alpinus* is found mainly above treeline (Rubidge 2010). Vegetation comprises roughly 40% of *T. speciosus* habitat

ground cover (Best 1994). *Tamias alpinus* favors areas with about 40% rocky ground cover (Clawson 1994).

Study sites

Study sites were located in Yosemite National Park (YNP) and Inyo National Forest, California (Figure 1). Sites ranged from 2400m to 3000m in elevation. Sites ranged from completely forested, to sparsely forested (near treeline), to un-forested, alpine environments (above treeline). In forested sites, lodgepole pine, mountain hemlock, and white pine were the dominant tree species.

Animal trapping

At each site, the research team (led by Tali Hammond and including 3-4 field assistants) laid out 2-7 grids consisting of 20-160 metal Sherman traps paired into trapping stations. The number of grids and traps varied based on particular site topology and characteristics. Traps targeted *T. alpinus* and *T. speciosus*, two sympatric species of chipmunks. Traps were baited with peanut butter and oats and were checked every 4-6 hours between dawn and dusk.

We recorded chipmunks by station, not individual traps. Successful stations caught 1-9 chipmunks. To simplify analysis, all successful stations were given a score of 1, indicating presence; unsuccessful stations were scored 0, indicating absence.

Vegetation surveys

To assess the habitats in each grid, we conducted vegetation surveys at trapping sites in 2013 and 2014 field seasons (May-September). There was some overlap in sample sites between years. We selected sites along an elevational gradient based on the literature and the results of previous trapping efforts. We conducted vegetation surveys at some (2013) or all (2014)

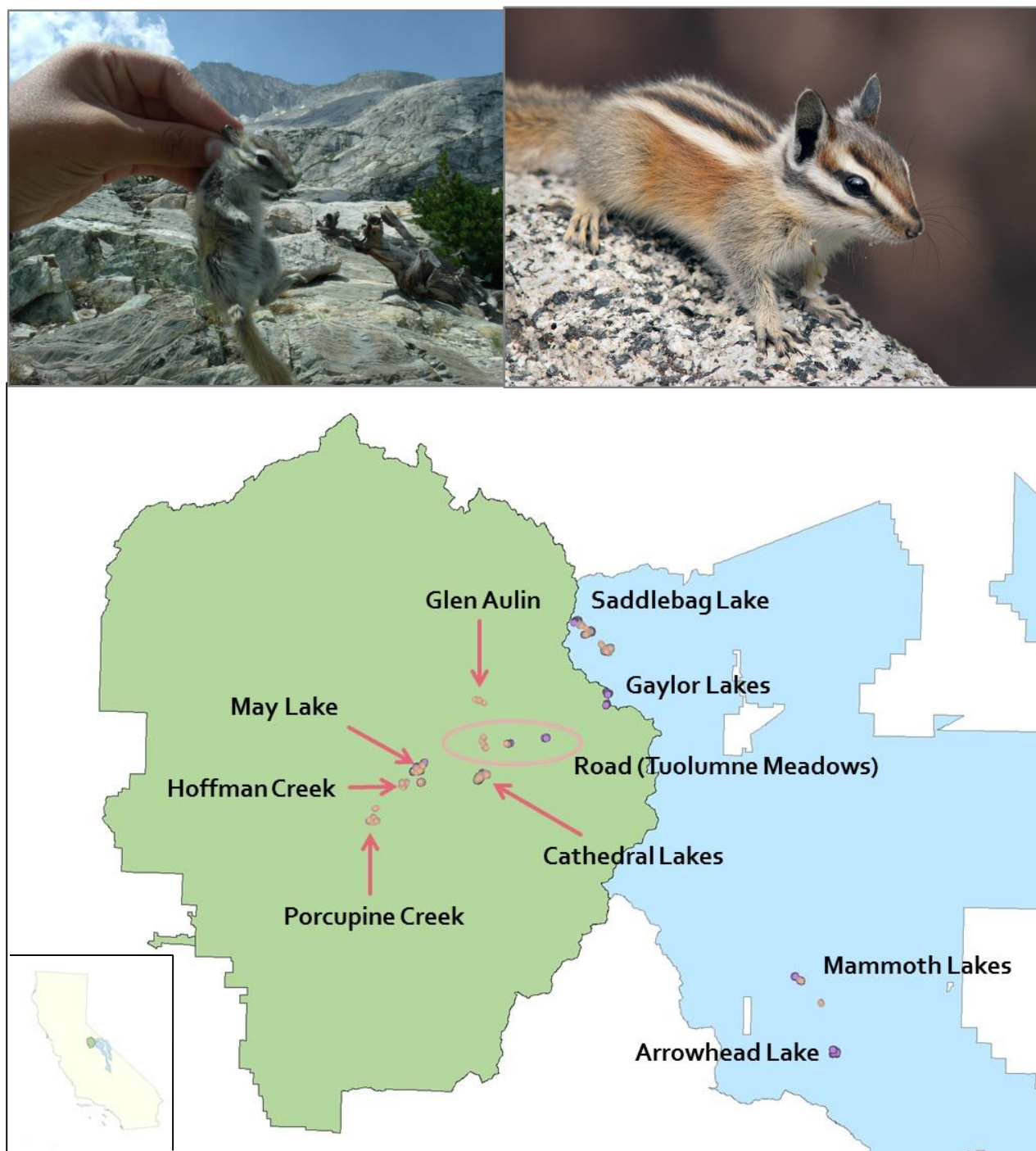


Figure 1: Focal species and map of all 2013 and 2014 study sites. Top left: *Tamias alpinus*, the alpine chipmunk. Top right: *Tamias speciosus*, the lodgepole chipmunk. Bottom: The green bounded area is Yosemite National Park and the blue bounded area is Inyo National Forest. Inset: the two parks' location in California. *T. speciosus* was present at all sites, but *T. alpinus* was only present at May Lake, Hoffman Creek, Glen Aulin, Cathedral Lakes, Gaylor Lakes, and Saddlebag Lake.

trapping stations. In both years, surveys consisted of a vegetation and ground cover survey, but the 2013 surveys were more extensive than in 2014 (Table 1). We geo-referenced all stations using a Garmin GPS. Survey methods were loosely based on the California Native Plant Society’s Rapid Assessment Protocol and on previous environmental surveys conducted for the same focal chipmunk species (DFS 2007). The ground cover portion of the surveys between the two years differed slightly, as detailed below.

Field survey data were based on estimates of ground cover percentage. Because of the imprecise nature of the surveys, occasionally, the total for a given station would sum to greater or less than 100 (see future limitations section for further discussion). I rescaled the numeric field estimates into to 100%. To determine which score type (numeric or percentage) performed better, I constructed models for each.

2013

In 2013, we conducted surveys at successful trapping stations, “edge” stations at the end of the grid, and randomly selected stations. We used ropes to mark the extent of survey plots. We estimated the portion of ground cover in the following categories: litter/duff, downed wood, shrubs, herbaceous, bedrock, boulders, large rocks, small rocks, bare soil and other. We recorded slope, aspect, and hydrologic and topographic characteristics. We identified the vegetation type using the Wildlife Habitat Relationship (WHR) system. We noted if there was evidence of humans

Table 1: Vegetation surveys by year. Left table shows parameters of the entire survey. Right table shows categories of the ground cover portion.

Category	2013	2014
Ground cover	X	X
Dominant ground cover species		X
Dominant tree species	X	X
Aspect	X	
Slope	X	
Hydrology	X	
Fire	X	
Human impact	X	X
Percent canopy cover	X	
WHR vegetation category	X	
Detailed tree survey (species, height, count, branching pattern)	X	
Photos	X	

Ground cover category	2013	2014
Litter/duff	X	X
Downed wood	X	X
Tree		X
Shrub	X	X
Herbaceous	X	X
Bedrock	X	X
Boulders	X	X
Large rocks	X	
Small rocks	X	X
Bare soil	X	X
Other	X	X

or fire. We identified the dominant tree species and estimated the percent canopy cover. We counted the number of trees in each survey grid and classified them by species, height, and branching pattern. Height was visually estimated in intervals of 5 meters (i.e., 0-5m, 5-10m, 10-15m, >15m), which was later resorted into a binary grouping of over or under 5 meters. Branching pattern was classified into 1, 2, and 3. Finally, photos were taken of each surveyed station from the four cardinal directions.

2014

In 2014, surveys were conducted at every station in the grid. We marked a square survey plot at each station using 15-foot ropes and visually estimated the percentage of the plot's ground cover in the following categories: litter/duff, downed wood, trees, shrubs, herbaceous, bedrock, boulders, small rocks, bare soil, and other. (The "tree" variable measured portion of the ground occupied by tree trunks, not the reach of the canopy.) Additionally, for each trapping grid we conducted one general survey of the most prevalent ground-cover and tree species types, as well as a garbage count. A single person conducted these broad-scale surveys, which involved a timed walk-through of every trap station in a given grid. The overall result was a quicker, yet less detailed vegetation survey.

GIS

To approximate the field surveys through digital mapping, I measured the following variables via GIS: distance to trails and roads, classification of ground cover, and normalized difference vegetation index (NDVI).

As a proxy for human impact, I calculated distance to closest trails or roads. I used three datasets to provide coverage of my entire study site: Yosemite trails, Yosemite roads, and Mono county roads (Figure 2). I used the "Near" function in ArcMap 10.2 (ESRI 2011) to find the distance from each trapping station to the closest trail and the closest road in meters .

For ground cover classification, I obtained orthoimagery from the National Agriculture Imagery Program (NAIP), dated 2010 and at 1-meter resolution. To approximate areas measured

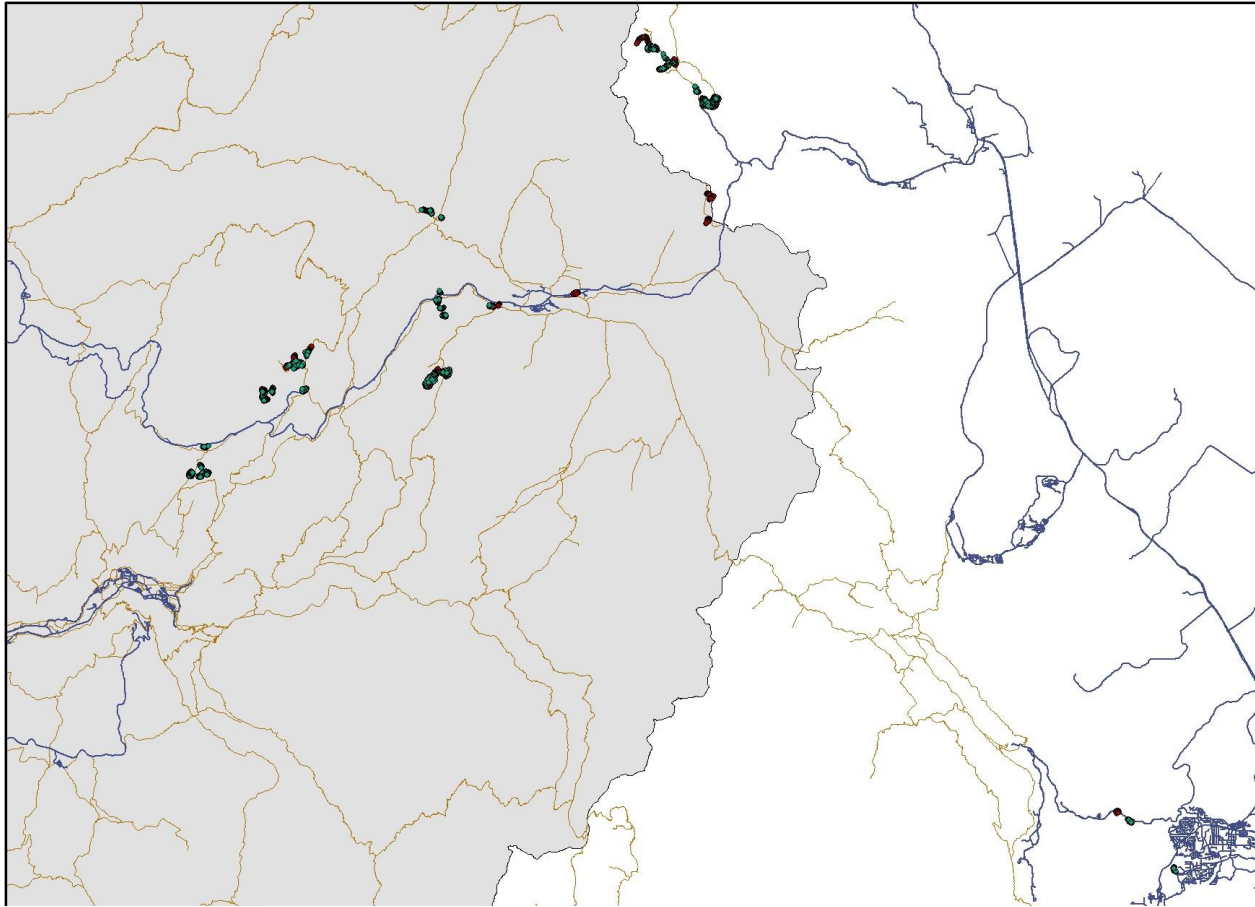


Figure 2: Traps, roads and trails. All trapping stations are shown in green (2013) and red (2014). Roads are shown in blue and trails in brown. The gray area is Yosemite National Park; the white area is Inyo National Forest and/or Mono County.

in field data, I created a buffer of 7.5 feet radius around each trap station in ArcMap. Each buffer zone contained 15-21 partial or whole pixels. I used ArcMap's Iso Cluster Unsupervised

Classification to classify the imagery into 6 categories based on spectral patterns. This tool uses Maximum Likelihood Classification, which assumes a normal distribution of the cells in each class sample and assigns each pixel to the class to which it has the highest probability of being a member (ESRI). Based on visual examination of the resulting classification, I defined the 6 classes as water, trees, grass, road/non-vegetated, dirt/non-vegetated, and rock/non-vegetated. (Figure 3). I then used the Tabulate Area function to count the number of pixels from each class per buffer zone. Finally, I converted the pixel numbers for each ground-cover class into percentages of the total buffer zone to make them more comparable to field surveys.

I also calculated average NDVI for each buffer zone. NDVI is a standard parameter that measures the "greenness" of an area based on reflectance in the IR and R bands. Values range

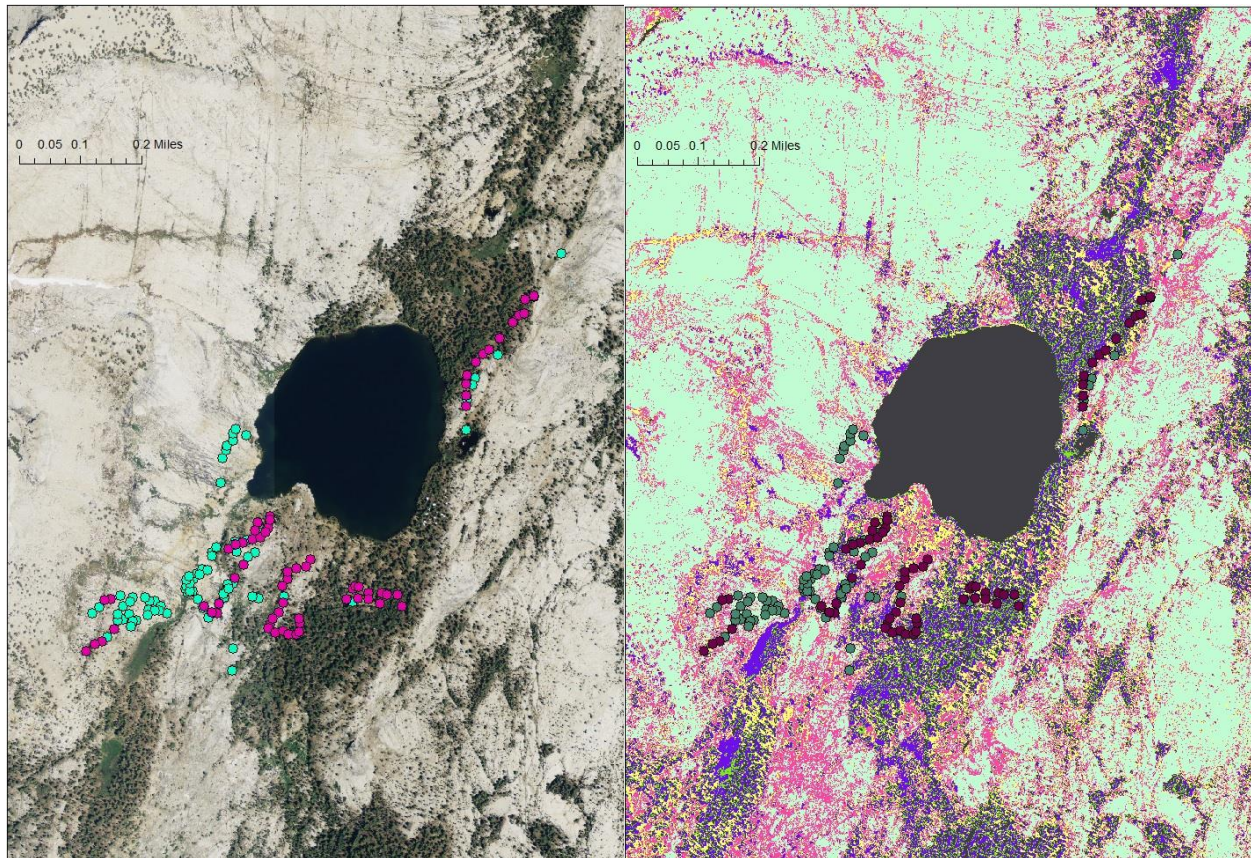


Figure 3: Classification of ground cover. The results of the classification are shown at May Lake. Successful *T. alpinus* traps are shown in green and successful *T. speciosus* traps are shown in pink (left) or red (right). The six classes were determined to be the following: water = black, trees = neon green, grass = purple, road = yellow, dirt = pink, rock = mint green.

from -1.0 to 1.0, where negative values mainly represent clouds, water and snow; values near zero mainly represent rock and bare soil; moderate values (0.2-0.3) represent shrub and grassland; and high values (0.6-0.8) indicate temperate and tropical rainforests (ESRI, Wittich and Hansing 1995). I used ArcMap's NDVI Image Analysis function to calculate the mean NDVI for each buffer zone.

Data analysis

To determine which ground cover variables most strongly impact chipmunk presence I ran a logistic regression based on the ground cover described above and trapping records from 2013 and 2014. I implemented the models in the statistical programs R and R Commander (R Development Core Team 2014, Fox 2005).

In ArcMap, each georeferenced trapping station was joined to field survey data, remote sensing classification, NDVI results, distance to trail, distance to road, presence of *T. alpinus*, and

presence of *T. speciosus*. As a preliminary analysis to identify potentially biologically relevant variables, I did a broad comparison of *T. speciosus* sites, *T. alpinus* sites, and mixed sites. Based on visual inspection of the resulting bar graphs, I selected a few parameters to test statistically. I used a Wilcoxon rank sum test, which is suitable for non-parametric data, to compare litter duff and bedrock in sites of presence for both species in both years.

I conducted a backwards stepwise logistic regression on 12 models predicting presence and absence. Different models were constructed for each species, year, survey type, and score type. I did a preliminary visual test for collinearity and found that there were no strong relationships between most variables. I built the final model using backwards deletion of non-significant explanatory variables. I used the Akaike information criterion (AIC) values to determine which models were most effective and to identify the most significant variables in each model.

RESULTS

There were statistically significant differences between *T. alpinus* sites and *T. speciosus* sites. Presence of chipmunks was significantly associated with several field and remote sensing variables, including bedrock, boulders, distance to trail, and NDVI (*T. alpinus*) and canopy cover, litter/duff, and NDVI (*T. speciosus*) (Table 2). In general, more variables were significant in the *T. alpinus* models. Likewise, the AIC values were higher for the *T. speciosus* models. The AIC values were higher in 2014 than in 2013. The percentage models tended to perform as well or better than the numerical models. Canopy cover was a significant predictor variable in all models in which it was measured; it was positively correlated with *T. speciosus* presence and negatively correlated with *T. alpinus* presence. Boulders and bedrock were the strongest positive predictors of *T. alpinus* presence. Litter/duff was the strongest predictor of *T. speciosus* presence.

Table 2. Predictor variables and AIC values of all 16 models. (Roman) text indicates a positive predictor while (*italics*) indicates a negative predictor. An asterisk (*) indicates a non-significant predictor variable.

Species	Year	Survey Type	Score Type	AIC	Predictor variables	
<i>T. alpinus</i>	2013	Field	Percentage	148	boulders, <i>downed wood</i> , bedrock, <i>canopy cover</i> , litter/duff	
			Number	155	<i>downed wood</i> , <i>canopy cover</i> , boulders, <i>shrub</i> , <i>large rocks</i> , bedrock	
	2013	RS	RS	633	rock, <i>trail</i> , grass, <i>distance to road</i> , NDVI	
			Mixed	Percentage	148	rock, <i>canopy cover</i> , <i>downed wood</i> , <i>shrub</i> , <i>large rocks</i> , bedrock, <i>herbaceous</i> , litter/duff, boulders, <i>bare soil</i> , grass
	2014	Field	Percentage	611	bedrock, shrub, small rocks, trail, herbaceous, boulders, distance to road*	
			Number	617	<i>litter/duff</i> , trail, <i>downed wood</i> , shrub, boulders, <i>herbaceous*</i> , bedrock*	
	2014	RS	RS	641	NDVI, distance to trail, <i>water</i> , <i>distance to road</i> , <i>trees*</i>	
			Mixed	Percentage	609	bedrock, shrub, small rocks, trail, herbaceous, boulders, NDVI, <i>distance to road*</i>
	<i>T. speciosus</i>	2013	Field	Percentage	278	canopy cover, distance to trail*, large rocks*
				Number	290	canopy cover, <i>downed wood*</i>
2013		RS	RS	717	Distance to road, rock, NDVI*, <i>distance to trail*</i>	
			Mixed	Percentage	282	NDVI, canopy cover, bare soil
2014		Field	Percentage	1054	litter/duff, bare soil, bedrock, <i>downed wood</i> , tree	
	Number		1068	litter/duff, <i>shrub</i> , <i>herbaceous</i> , boulders, tree, bare soil*, <i>small rocks*</i>		
	RS	RS	1128	water, NDVI, tree*		
2014	Mixed	Percentage	1054	Litter/duff, bare soil, bedrock, <i>downed wood</i> , tree		

Inter-site differences

I found that sites exhibited marked difference in habitat structure, which is related to species presence. The sites were highly significantly different for all comparisons in the expected directions. In both 2013 and 2014, stations where *T. speciosus* were present had significantly higher percentages of litter/duff ground cover than *T. alpinus* (Wilcoxon rank sum tests, 2013: $W = 1164$, $p = 6.14 \times 10^{-10}$; 2014: $W = 7287.5$, $p < 2.2 \times 10^{-16}$). Similarly, in both 2013 and 2014, stations where *T. alpinus* were present had significantly higher percentages of bedrock ground cover than *T. speciosus* (Wilcoxon rank sum tests, 2013: $W = 4261$, $p = 2.361 \times 10^{-8}$; 2014: $W = 41361.5$, $p < 2.2 \times 10^{-16}$).

These patterns are present at the scales of station, grid and site. Within individual sites, grids could be *T. speciosus* only, *T. alpinus* only, or mixed. Anecdotally, *T. speciosus*-only grids tended to be forested, while *T. alpinus*-only grids were rockier and more open. In the vegetation surveys, these differences were apparent in higher portions of litter/duff in *T. speciosus*-only grids and higher portions of bedrock and boulders in *T. alpinus*-only grids. Two grids at the May Lake site illustrate this pattern (Figure 4). At the site level, sites with only *T. speciosus* (MA, site1, AL, PC, RD) had higher portions of litter/duff. Sites with both species (ML, CL, GL, SL, GA, HC) were more heterogeneous (Figure 5). There were no sites with only *T. alpinus*.

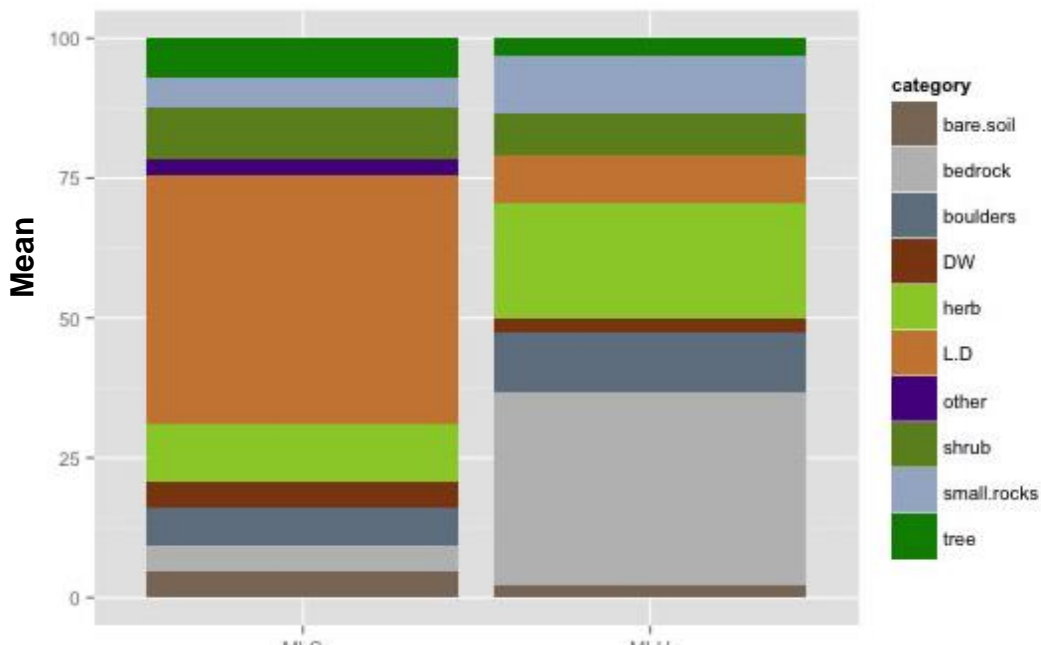


Figure 4. Average ground cover characteristics at two May Lake grids. MLC was *T. speciosus* only. MLH was *T. alpinus* only.

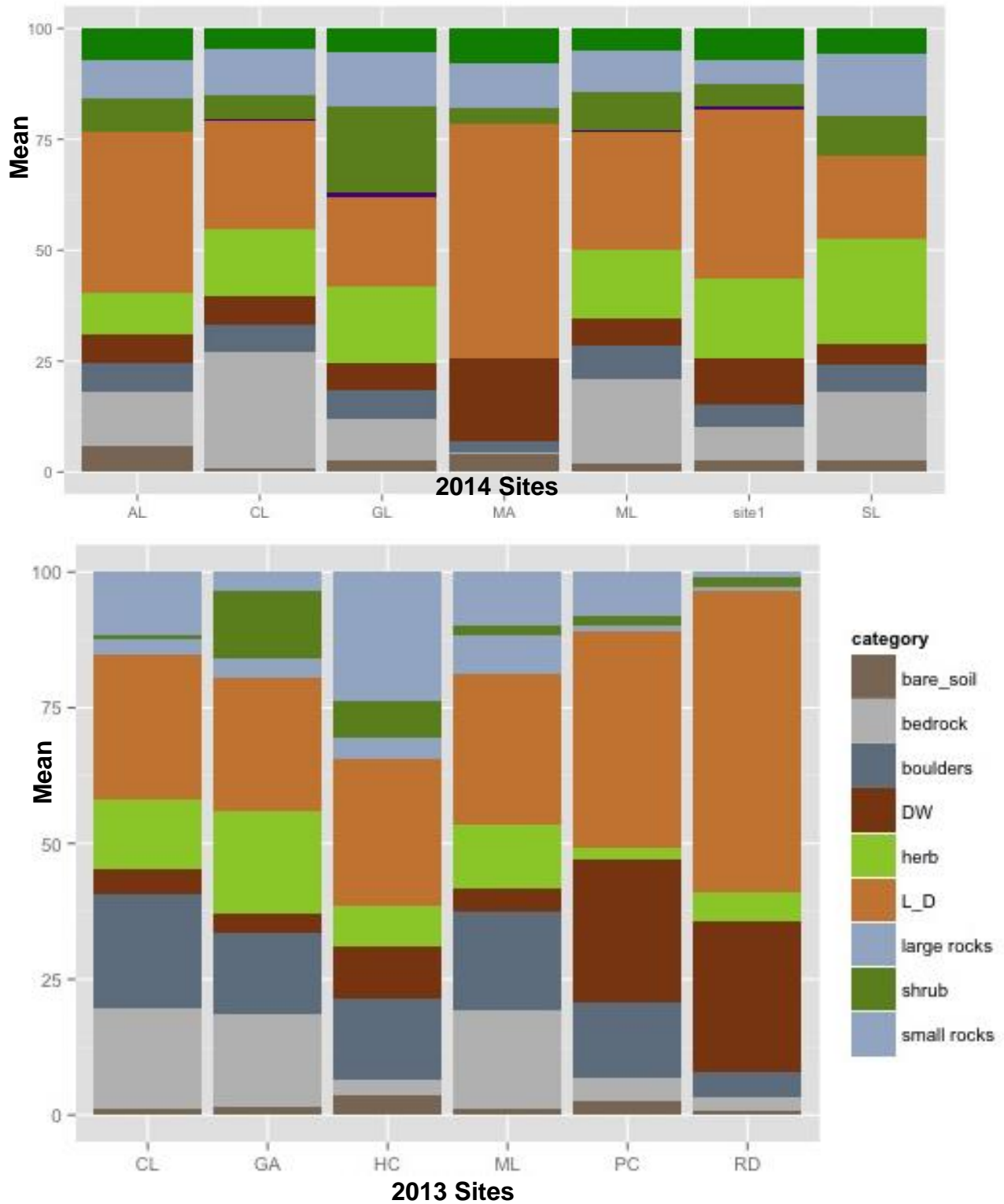


Figure 5. Average ground cover characteristics across 2014 sites (top) and 2013 sites (bottom). 2014 sites AL, MA, and site1 and 2013 sites PC and RD were *T. speciosus* only. All other sites were mixed. (Note that 2013 RD and 2014 site1 had a high degree of overlap.)

Field data models

The field data models revealed significant relationships between ground cover variables and chipmunk presence for both species. For *T. alpinus*, bedrock and boulders were significant variables across both years. Canopy cover was a negative predictor of *T. alpinus* presence in 2013; this variable was not measured in 2014. For both 2014 models, distance to trail was a positive predictor, though it did not appear in the 2013 models (Figure 6).

For *T. speciosus*, canopy cover was the only significant predictor of presence in 2013; it was not measured in 2014. It was a positive predictor of *T. speciosus* presence. Litter/duff was a significant predictor in both 2014 models (Figure 7).

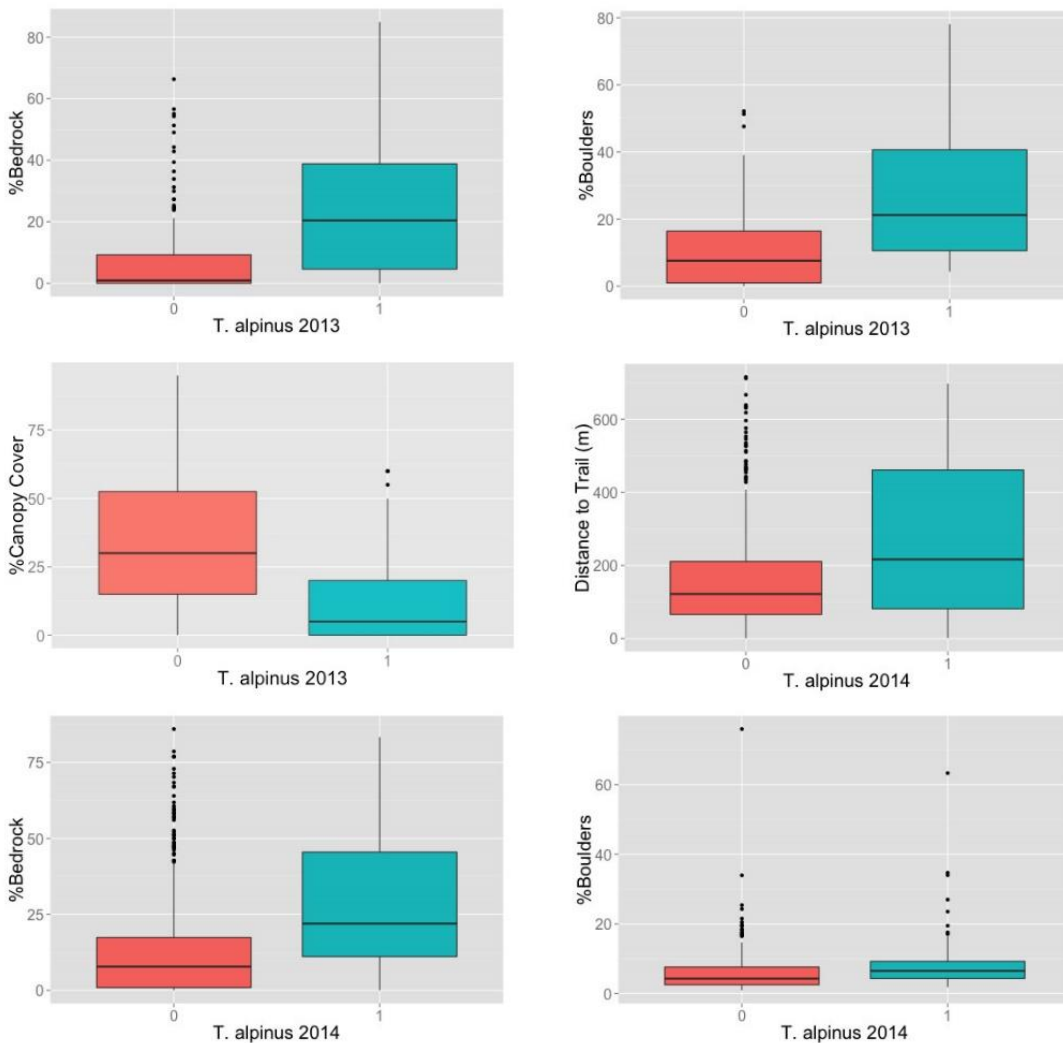


Figure 6. Boxplots from *T. alpinus* field models.

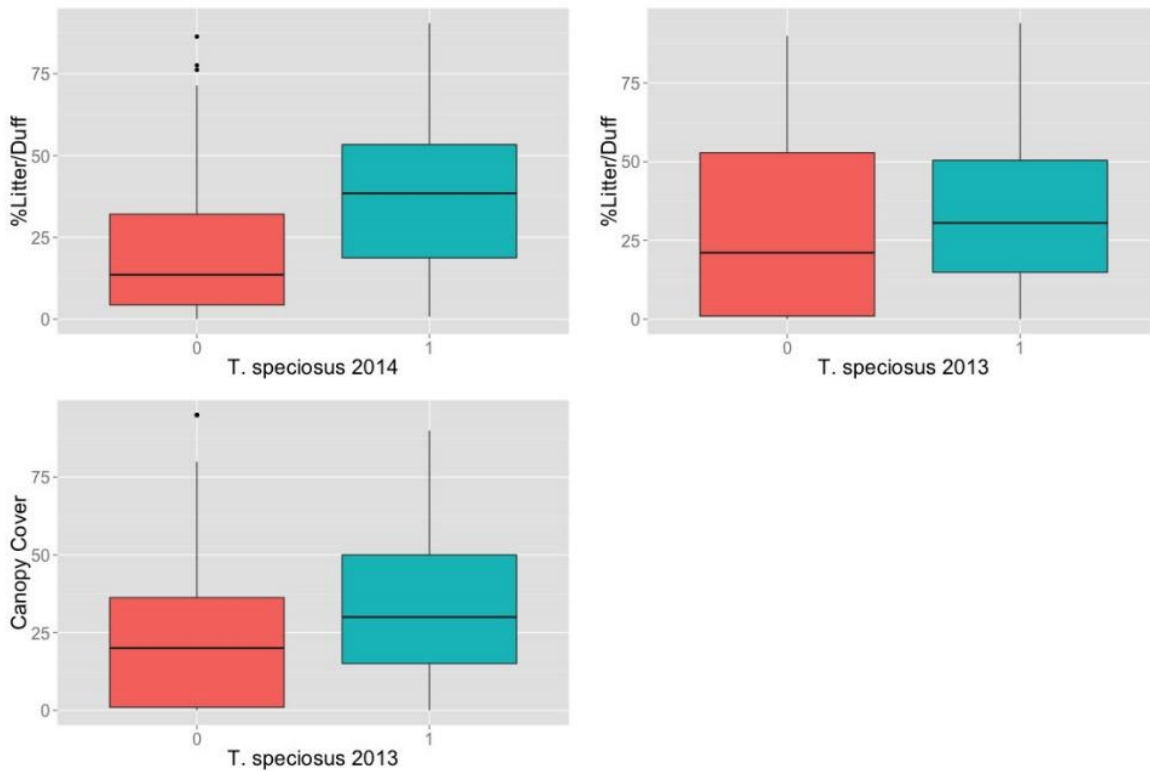


Figure 7. Boxplots from *T. speciosus* field models.

Remote Sensing RS models

The quality of RS models varied between years (Table 2). In 2013, the RS model performed more poorly than field data models for both species. In 2014, the RS and field data models performed similarly in terms of AIC value. For *T. alpinus*, distance to trail was a positive predictor in 2014 (mirroring the results of the field data model), but a negative predictor in 2013. NDVI and distance to road were negative predictors of *T. alpinus* presence in both 2013 and 2014 (Figure 8). For *T. speciosus*, there were few similarities between years. NDVI appeared as a positive predictor in both years, but it was not significant in 2013. In 2013, distance to road (positive) and rock (negative) were the significant predictors. In 2014, water and NDVI were the significant predictors.

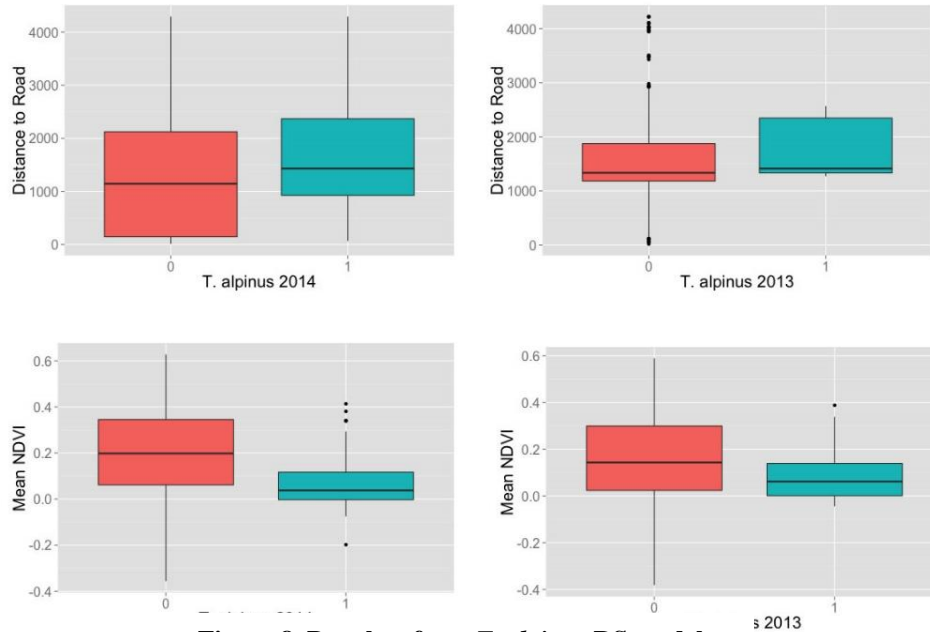


Figure 8. Boxplots from *T. alpinus* RS models.

DISCUSSION

The models showed a clear difference in habitat preferences between *T. speciosus* and *T. alpinus*. Models generally performed better for 2013 over 2014 data and better for field data over RS data. RS data, such as distance to trail and distance to road, often provided conflicting results between models, suggesting that RS methods could be improved. Preliminary results of models incorporating both RS and field data show only minor improvements over field-only models.

T. speciosus and *T. alpinus* models

Habitat differences between and within sites matched known expectations of habitat preferences for each species. In my data analysis, I found that the differences between sites were statistically significant, with a higher portion of litter/duff at sites of *T. speciosus* presence and a higher portion of bedrock at sites of *T. alpinus* presence. Although there were no *T. alpinus*-only sites, there were several single-species grids. In general, *T. alpinus*-only grids had higher portions of bedrock and lower portions of litter/duff than *T. speciosus*-only grids. These grids suggest an open, rocky habitat. These trends follow anecdotal experience from field research.

The predictors for *T. alpinus* matched expectations from the literature. Bedrock and boulders were positive predictors and canopy cover was a negative predictor; when considered together these relationships indicate an open, rocky environment. This preference matches anecdotal experience and expectations from the literature (Clawson 1994). Similarly, NDVI had a negative relationship with *T. alpinus* presence. A low or negative NDVI indicates a low degree of vegetation, such as rocks or bare soil.

The results of the human impact variables differed between *T. alpinus* models. Distance to road was a negative predictor of *T. alpinus* presence, indicating that chipmunks were more likely to be found closer to the road. This result contradicted my experience in the field; *T. alpinus* tend to live in remote areas, especially compared to *T. speciosus*. This phenomenon could be explained by the high success at Saddlebag Lake (SL), which also happened to be closer to roads than other sites where *T. alpinus* occurred.

Interestingly, although distance from trail was a positive predictor in all three 2014 *T. alpinus* models, indicating that *T. alpinus* were more likely to be found farther away from trails, it was negative for 2013 RS, and not predictive in either 2013 field survey model. This discrepancy could be a result of inter-year differences in specific trapping localities. In 2014, we visited a new *T. alpinus*-only grid (SHL) in the Saddlebag Lake site, which was farther from the trail. In 2013, we spent more time at a grid (SLP) with high *T. alpinus* trapping success that was closer to a trail.

Canopy cover and litter/duff were the most significant predictors for all *T. speciosus* models, confirming expectations based on the literature and anecdotal experience (Best 1994). In general, the *T. alpinus* models had a higher number of significant variables than the *T. speciosus* models. In addition, the AIC values were higher for *T. speciosus* models, indicating a model with weaker explanatory power. One explanation for this is that *T. speciosus* is a generalist, making it harder to identify which variables carry the most weight, whereas *T. alpinus* has narrow habitat preferences, making it easier to identify significant variables (Best 1994, Clawson 1994).

RS vs field models

AIC values were consistently lower for field data models in comparison to remote sensing models, indicating that less variation could be explained by remote sensing data. The differences were especially large between the 2013 RS and 2013 field data models. This may be a result of the limitations of the remote sensing process.

Canopy cover was consistently a strong predictor variable in the field data models. In the *T. alpinus* models, it was always a negative predictor; in the *T. speciosus* models, it was always a positive predictor. Canopy cover was not measured in 2014, but its consistent significance suggests it may be worth re-incorporating into vegetation surveys in upcoming field seasons. Because canopy cover measures the density of vegetated tree cover, it would make sense for a similar parameter in the RS models to explain significant variation in chipmunk trapping success. For instance, both NDVI and the RS class “trees” measure a similar parameter to canopy cover. Although NDVI was significant in 3 out of 4 models, the “trees” parameter (estimated by RS) was surprisingly never a significant variable. This may indicate errors in the classification. For instance, pixels containing trees may have appeared lighter or darker based on vegetation density, shadows and other effects. Thus the “true” tree pixels may have been spread across the two vegetation classes (trees and grass), diluting the predictive power of trees. Furthermore, the classification may have made errors in distinguishing between highly shadowed areas, which are common in mountainous regions, and dense vegetation

Although remote-sensing-based models underperformed here, it is worth noting that a very simple remote sensing methodology was used in this case. Specifically, we used an unsupervised method that assigned pixels to classes using a maximum likelihood decision making process (ESRI 2015). More advanced methods, including image pre-processing and the inclusion of supplemental information such as elevation, can improve the quality of the classification (Trodd 1996). The issue of elevation is particularly important in mountainous areas, where hillshade can significantly alter results; steep, mountainous slopes can create shadows, which may cause errors in classification. In a supervised method, the user creates several training areas to “teach” the program patterns for each class. This method is more capable of accurately describing mixed zones, such as heterogeneous areas or transition areas, including meadow edges. A supervised RS system may have improved the accuracy of classification in this study (Trodd 1996).

The efficacy of RS data to answer research questions depends on the scale of data used. For instance, state-wide data may be effective at examining patterns of drought on agricultural

lands or the history of forest clear-cutting. RS is particularly effective for answering large-scale questions like these due to the cheapness and efficiency with which low-resolution data can be collected for a broad area. Although classification is adept at identifying broad trends in the landscape, it cannot capture all the nuances of landscape at very large (high resolution) scales (Trodd 1996). Chipmunks use the landscape at a scale smaller than the 1-meter resolution provided by NAIP imagery. This limits our abilities to draw conclusions about chipmunks' patterns of microhabitat use using low-resolution RS data (Ly 2012). The recent growth of drones as a research tool could have powerful impacts on collecting high-resolution data of remote areas. Potentially, researchers could use drones to obtain extremely localized, high-resolution data of their study sites. There are a variety of technologies, such as profiling radar, scanning lasers, and imaging spectrometers, that could collect these kinds of localized data. However, comparisons are needed among the performance of these instruments to assess information content and accuracy (Hyypä et al. 2000). In general, RS is under the burden of proof to rise to the standard set by field-collected data, and more comparisons remain to be made between the two methods.

Limitations and future directions

Field survey data was gathered by estimating percentages, as described above. The total amount of ground cover for a given station frequently summed to greater than 100%. A total over 100% is justified in some cases (i.e., low-lying shrubs and litter/duff might overlap, but were both counted in the survey because both have an impact on chipmunk habitat use). However, the high occurrence of totals over 100% indicates the potential of human error. To standardize our data, we ran models with the true numbers and with numbers re-scaled to 100. This standardization had an effect on the model output. For instance, in the 2013 *T. alpinus* models, litter/duff was predictive only in the percentage model, and shrub and large rocks were predictive only in the numerical model. Models for the other species and years had similar inconsistencies between numerical and percentage models. In general, the percentage models performed as well as or better than the numerical models.

My statistical analysis did not include interaction terms. The number of potential interaction terms was prohibitively high for the scope of this project. Future work could account

for interactions between different predictor variables, which might have significant effects on the models. For example, it is possible that *T. speciosus* uses bedrock, but only when there is high vegetation, or that *T. alpinus* uses herbaceous areas only when there is little tree-cover. Additional environmental parameters, including slope, elevation and aspect, could also affect model results.

Future research on the elevational range shifts in YNP should investigate the potential interaction terms. Of particular interest is the potential interaction between habitat preferences and human impact. At what degree of human impact do chipmunks start compromising their preferred habitat? In addition to the human impact terms incorporated in this study (distance to trail, distance to road), future analyses could include other parameters like trash count or number of cars in parking lots close to sites. Trash count, in particular, could help delineate the differences between sites roads close to campgrounds versus relatively remote highways, which are differentially used by humans.

Analysis of interaction terms could point towards more complex habitat preferences, but were not taken into account in this study. Additionally, it is likely that more sophisticated mixed models incorporating random variables as well as fixed variables may have more explanatory power for predicting chipmunk presence. In this study we used only fixed variables; however, future studies could incorporate a mixed structure and include date or chipmunk individual ID as random predictor variables. In general, more thorough understanding of complex habitat dynamics would improve conservation planning.

Future research could take several directions. The results of this project indicate several potential improvements for field surveying methods. The repeated significance of canopy cover suggests that this parameter should be re-incorporated into field surveys in upcoming seasons. Furthermore, tree portion was not measured in 2013 and large rocks portion was not measured in 2014; both of these variables exhibited strong relationships in multiple models, suggesting that both should be measured in all future surveys.

As described above, future comprehensive projects could more fully evaluate the relationship between field data and remote sensing data by using more advanced remote sensing methods and/or accounting for interaction terms. Additionally, a model incorporating both RS and field data could be more fully developed. My preliminary results suggest this does not improve the model dramatically (see AIC values of mixed models in Table 2), but it is possible that more

advanced remote sensing technologies could capture important predictors that may enhance the field-collected data.

Models might perform differently when using trapping frequency data, rather than binary presence or absence data. Successful stations caught between 1-9 chipmunks. There might be significant differences in ground cover between a low-success trap and a high-success trap. Results of such an analysis could have impacts on future field seasons, when researchers make decisions about where to trap.

Other potential analyses could split presence/absence differently, e.g. by sex, age, or fecal stress hormone level. Trapping success may be influenced by chipmunk sex because trapping occurs during breeding season. Females with young may be more constrained in where they spend their time due to a need to stay close to their burrow. Alternatively, females may have a higher need for food due to increased metabolic needs from lactation (Veloso et al. 2002).

Similarly, there may be differences in trapping success based on age. Anecdotally, juvenile chipmunks were often caught in high volumes in adjacent traps. It is possible that groups of juveniles caught close together were siblings caught close to their burrow, which might affect the degree of variation of ground cover. At the other end, old chipmunks (>2 years) may have slightly different habitat preferences; perhaps their longevity is connected to their ability to avoid predators or locate food sources. However, it may be difficult to confidently identify chipmunk age. Our primary method of determining age of adults is by using trapping records from previous years and is dependent on ear tags staying in place for multiple years. We cannot definitively identify the age of adult chipmunks in their first year caught.

Fecal stress hormones may be correlated with different rates of trapping success. Higher fecal stress hormone levels have been correlated with higher activity levels in the past (Cote et al. 2006). Thus, it is possible that chipmunks with higher stress levels might have larger ranges, potentially with more variance of ground cover. This idea could be further elaborated through the use of accelerometers (currently in development). Likewise, stress levels may also be connected to behavior (Montiglio et al. 2012), which was measured during standard chipmunk processing in 2013 and 2014. Chipmunk behavior was classified as “bitey,” “twisty,” “screamy” or “calm”. Preliminary results suggest that “calm” behavior was actually linked to higher stress levels. Future models could evaluate stress levels as a function of habitat. For instance, perhaps chipmunks have higher stress levels when they are outside of their preferred habitat.

Broader implications

Further comparisons between field surveys and RS methodologies are still needed. RS models should continue to be developed to improve efficiency of surveys. In particular, high resolution RS data, capable of delineating microhabitats, has huge potential relevance for studies of conservation and climate change at various scales. For instance, the finding that microtopography can mimic the differences of large elevational gradients over short horizontal differences means that species do not necessarily need to climb several hundred meters in elevation to escape warmth (Scherrer and Körner 2010). Especially in remote and inaccessible montane environments, RS has the potential to be a powerful tool in collecting data on such micro-differences in landscape. RS is a rapidly developing technology and could have wide-ranging impacts on conservation goals.

A reduction of time spent conducting field surveys would allow researchers to spend more time in the field directly working with chipmunks, i.e. gathering more fecal stress hormone data. The outcomes of such research could lead to improved knowledge of the mechanisms of range shifts in alpine species. The results of this study support the idea that *T. alpinus* is a specialist and *T. speciosus* is a generalist; these tendencies may influence the species' range shift responses. For instance, perhaps *T. speciosus*' ability to survive in a range of conditions enables it to maintain its historical range, while *T. alpinus*' stronger preferences require it to "follow" its ideal conditions upwards in elevation. The particular dynamics of the relationship between these two species—their biological similarity, yet differing responses to climate change—make them a model system for understanding heterogeneity in biotic response to climate change. It is important to understand how and why animals live where they do in the context of predicting future species distributions. Understanding the mechanisms and spatial patterns of change can have profound impacts on conservation.

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