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Mapping and monitoring Mount Graham red squirrel habitat with Lidar and Landsat imagery

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ABSTRACT

The Mount Graham red squirrel (*Tamiasciurus hudsonicus grahamensis*) is an endemic subspecies located in the Pinaleño Mountains of southeast Arizona. Living in a conifer forest on a sky-island surrounded by desert, the Mount Graham red squirrel is one of the rarest mammals in North America. Over the last two decades, drought, insect infestations, and fire destroyed much of its habitat. A federal recovery team is working on a plan to recover the squirrel and detailed information is necessary on its habitat requirements and population dynamics. Toward that goal I developed and compared three probabilistic models of Mount Graham red squirrel habitat with a geographic information system and logistic regression. Each model contained the same topographic variables (slope, aspect, elevation), but the Landsat model contained a greenness variable (Normalized Difference Vegetation Index) extracted from Landsat, the Lidar model contained three forest-inventory variables extracted from lidar, while the Hybrid model contained Landsat and lidar variables. The Hybrid model produced the best habitat classification accuracy, followed by the Landsat and Lidar models, respectively. Landsat-derived forest greenness was the best predictor of habitat, followed by topographic (elevation, slope, aspect) and lidar (tree height, canopy bulk density, and live basal area) variables, respectively. The Landsat model's probabilities were significantly correlated with all 12 lidar variables, indicating its utility for habitat mapping. While the Hybrid model produced the best classification results, only the Landsat model was suitable for creating a habitat time series or habitat–population function between 1986 and 2013. The techniques I highlight should prove valuable in the development of Landsat- or lidar-based habitat models range wide.

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1. Introduction

The sky-island archipelago in the American Southwest is comprised of a series of mountain ranges that have unique ecosystems and wildlife that are isolated from one another due to lower-elevation deserts that surround them. One of the largest sky-island mountain ranges is the Pinaleños, located in Coronado National Forest in Southeast Arizona. The Pinaleños are home to five federally listed threatened and endangered species, 18 endemic species, and 57 sensitive taxa (USFS, 1999; Jones, 2009). The Pinaleños are a microcosm of anthropogenic factors that have created unhealthy forests during the last century in North America, highlighting the negative effects of livestock grazing, road building, logging, and active fire suppression (Swetnam et al., 2009). It is thought that wildfires used to occur primarily as small, patchy fires in the Pinaleños, with larger stand replacing fires occurring every 300–400 years (Stromberg and Patten, 1991), but active fire suppression over the last century has increased fuel loads, making larger, more frequent fires more likely (Swetnam et al., 2009).

The North American red squirrel (*Tamiasciurus hudsonicus*) inhabits coniferous and mix-coniferous forests throughout much of North America, eating seeds and fungi. Extremely territorial, red squirrels have territories that range in size from ~0.5 to 5 ha, where they cache food in piles (middens) on the forest floor, defending them year round (Munroe et al., 2009; Blount and Koprowski, 2012). Common throughout most of its range, the American red squirrel became isolated in the Pinaleños at the end of the Pleistocene when the climate warmed. Restricted to higher elevations (>2353 m) where spruce-fir and mixed-conifer forests have existed for at least 9000 years (Anderson and Smith, 2009), a distinct subspecies, called the Mount Graham red squirrel (*Tamiasciurus hudsonicus grahamensis*), developed (U.S. Fish and Wildlife Service, 1992; Sullivan and Yates, 1995). The Mount Graham red squirrel (MGRS) was thought extinct in the 1960s (Minckley, 1968) but it reappeared in the 1970s (Brown, 1984). However, due to its isolation and small numbers, it was declared endangered in 1987 (*Federal Register* 52(106), 3 June 1987).

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In the 1990s a series of insect infestations occurred in the Pinaleño Mountains. Geometrid moths and bark beetles began killing corkbark fir (*Abies lasiocarpa* var. *arizonica*) and Engelmann spruce (*Picea engelmannii*), with over 99% of MGRS middens in the spruce-fir forest showing evidence of spruce aphid infestation in 2000 (Jones, 2009; Koprowski et al., 2005). Following insect infestations, the Nuttall Fire burned approximately 12,000 ha of scrub oak and conifer forests during June–July 2004 (Leonard and Koprowski, 2010). The fire's intensity was uneven, with MGRS remaining in low-moderate intensity burn areas composed of mixed-conifer forest, while opportunistically foraging in higher-intensity burned spruce-fir forest (Blount and Koprowski, 2012; Leonard and Koprowski, 2010). There were around 350 MGRS between 1991 and 1997, which increased to around 600 in 1999, before dropping down to around 250 after the Nuttall fire (Snow, 2009).

Due to the extremely rugged character of the Pinaleño Mountains and the imperilment of MGRS, numerous spatially explicit models of MGRS habitat and population dynamics models have been developed (Hatten, 2000; Pereira and Itami, 1991; Rushton et al., 2006; Wood et al., 2007). Pereira and Itami (1991) developed a logistic model that uses forest stand maps and topographic information to predict the likelihood of MGRS habitat. The model produced good estimates of habitat quantity and suitability, but it required forest inventory (e.g., tree density) data collected in the field, where conditions change quickly, restricting its utility. Hatten (2000) developed a remote sensing model (unsupervised classification on 5 bands + NDVI) that estimates MGRS habitat with Landsat Thematic Mapper imagery (30-m resolution) and topographic data. The remote sensing model uses pattern recognition and Landsat TM imagery to identify structural and spectral properties of forests that MGRS inhabit, making it ideally suited for change detection. This model identified 3769 ha of potential MGRS habitat in 1993, which decreased 8% by 2003 due to insects and fire (Hatten, 2009). Unfortunately, the Pattern Recognition Model is rule-based and can only distinguish between unsuitable and suitable areas, but researchers have found that moderately burned forests can support MGRS while severely burned areas rarely do (Blount and Koprowski, 2012), thereby limiting its utility. Wood et al. (2007) used high resolution (2.4 m) QuickBird satellite imagery (DigitalGlobe, Inc., Longmont, CO) to characterize MGRS habitat with 9 land-cover classes. Wood et al. (2007) found that a 28-m radius provided the best classification results, with MGRS middens located in higher seed production sites that occurred in healthier, thicker trees. While the model is very accurate (90%), it requires costly high-resolution satellite imagery and generation of multiple land-cover classes to operate, restricting its utility. Rushton et al. (2006) used different life-history scenarios to model the MGRS population between 1991 and 2004, explaining 67% of the variability, concluding that the most important need is to understand relationships between MGRS and habitat at a local scale.

The goal of this project was to inform management agencies about MGRS habitat and population trends with a cost effective and easily applied Landsat model. The previous MGRS models provided a foundation for a new probabilistic modeling approach that can be projected through space and time at 30-m resolution with free Landsat imagery, updated every 16 days, available since 1984. Specifically, this study had four objectives: (1) develop a probability model that can remotely identify and monitor MGRS habitat, (2) create a habitat time series between 1986 and 2013, (3) quantify changes in MGRS habitat between 1986 and 2013, and (4) develop a habitat–population function that captures the relationship between MGRS population estimates and predicted habitat. Information from this analysis will be useful to the MGRS Recovery Team and U.S. Forest Service in the development of habitat management and recovery plans, as well as providing useful modeling techniques for assessing changes in wildlife habitats remotely throughout the sky-island archipelago of the southwestern US.

2. Materials and methods

2.1. Study area

The Pinaleño Mountains, located in Graham County (Fig. 1), trend northwest to southeast for approximately 35 km, are less than 20-km wide, and have an extensive high-elevation plateau, reaching a height of 3268 m (Hatten, 2009). There are 4097 ha of terrain above the 2744-m (~9000 ft) contour, and 538 ha above the 3049-m (~10,000 ft) contour, supporting one of the southern-most spruce-fir forests in North America. The northwest/southeast orientation of the Pinaleños creates aspects that generally face northeast or southwest, creating temperature differences that influence the distribution of plants and animals. The topography inside the MGRS survey boundary is gentle compared to the steep slopes that fall sharply away from the upper plateau.

The MGRS survey boundary encircles 4823 ha of mountainous terrain that is covered in mixed conifer, ecotone, and spruce-fir forests found largely above the 2744-m contour. Divided into 21 survey units, the MGRS survey area has three distinct habitat types (Snow, 2009). The mixed-conifer habitat type includes Douglas-fir (*Pseudotsuga menziesii*), white fir (*Abies concolor*), southwestern white pine (*Pinus strobiformis*), limber pine (*Pinus flexilis*), and ponderosa pine (*Pinus ponderosa*). Dominant tree species in the spruce-fir habitat type include Engelmann spruce (*P. engelmannii*), subalpine fir (*A. lasiocarpa*), blue spruce (*Picea pungens*), and aspen (*Populus tremuloides*). In contrast, the ecotone habitat type is a transition zone found between the lower mixed conifer and higher spruce-fir forests and contains plant and animal species common to both forest types.

2.2. Modeling overview and environmental database

I developed and compared three spatially explicit (GIS-based) probability models of MGRS habitat (as characterized in this study by recently active middens) with logistic regression and a geographic information system (GIS). Toward this objective, I developed an environmental database comprised of presence/absence data (locations of recently active middens versus absence locations), topographic data, vegetation greenness obtained from Landsat Thematic Mapper imagery, and 12 forest variables extracted from a light detection and ranging (lidar) survey (Mitchell et al., 2012). Each model contained the same set of topographic variables (variables shown in caps) extracted from a 30-m resolution digital elevation model (DEM): slope (SLOPE), aspect (ASPECT), and elevation (ELEV), plus a unique set of forest variables. The first model I created (Landsat) contained the three topographic variables and a greenness variable (Normalized Difference Vegetation Index [NDVI]), since it correlates with vegetation lushness, vigor, and forest health (Williams et al., 2013), and has been found to be an important predictor of MGRS habitat (Hatten, 2000; Wood et al., 2007; Hatten, 2009). I extracted NDVI from the USGS Landsat archive, utilizing Landsat 5 data from 1984 to 2011, Landsat 7 data for 2012, and Landsat 8 data for 2013.

The second model (Lidar) I created contained the three topographic variables and 12 lidar-derived forest variables: biomass (BIOM), canopy fuel load (CFL), canopy base height (CBH), canopy bulk density (CBD), total basal area (TBA), live basal area (LBA), total volume (TVOL), dead volume (DVOL), Lorey's mean height (LMH), quadratic mean diameter (QMD), standard deviation of tree height (SDTH), and stand density index (SDI). Each lidar variable