ASSESSING GRAZING IMPACTS ON A TROPICAL DRY FOREST SYSTEM IN MADAGASCAR THROUGH VEGETATION, SATELLITE IMAGE, LEMUR OCCUPANCY, AND ACOUSTIC ANALYSIS

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Abstract

The ability to assess the quality or ecological value of a landscape is a useful tool in effective conservation and natural resource management. Ecosystem biodiversity and functionality are reduced when human activities cause habitat alteration and/or fragmentation. Compromised habitats are unlikely to support naturally occurring communities or healthy ecosystem functions. Conservation scientists have historically concentrated their efforts on large, intact habitats with little human disturbance; the conservation value of small and/or disturbed areas has been comparatively overlooked. One limitation may be a lack of tools to identify disturbed areas with conservation value. Techniques that allow researchers to assess the habitat quality of disturbed-but-functioning areas with conservation potential are especially useful in a threatened ecosystem like the tropical dry forests (TDFs) of Madagascar.

Madagascar has an extremely high number of endemic species -- species unique to the large island nation -- as well as widespread impacts from human activities. This has resulted in large swaths of disturbed habitat across the vast majority of the island’s landscapes. A variety of forest types are found in Madagascar including: evergreen (coastal forest, low altitude, mid altitude, and lower montane rainforest, montane scrubland, and woodland), deciduous (coastal, western seasonally deciduous, and southern dry deciduous forest), mangrove, and marshland (DuPuy and Moat 1996). The southern tropical dry forest makes up about 1400 km$^2$ or 15% of the forest cover in Madagascar. This forest is used for agriculture and forest product extraction but is mostly impacted by livestock grazing. Given that the vast majority of remaining forests in this region are unprotected, it is likely that the forests in the region are grazed and have been for many years.
We evaluated the effects of livestock on the tropical dry forest through vegetation, satellite, lemur occupancy, and acoustic sampling at 24 sites within the Beza Mahafaly Special Reserve. Sites were divided between two forest types (gallery and dry deciduous) and three levels of grazing intensity (ungrazed, moderately grazed, and heavily grazed). Canopy and understory measurements varied significantly by forest class and grazing intensity. Land cover classification using satellite imagery resulted in highly accurate assignment of forest class and grazing presence, but not grazing intensity. Lemur occupancy varied by forest class, yet grazing presence resulted in lower occupancy in only one of two lemur species sampled. Biological sound activity was significantly different by season, yet did not differ by forest class or grazing intensity. The effects of grazing on vegetation and wildlife appear to be greater in the dry deciduous forest than in the gallery forest. Remote monitoring methods used in this study are promising for future monitoring schemes and land management decisions.
Chapter 1
Introduction

Background

Tropical dry forest (TDF) is found in areas with warm year-round climates, brief periods of rainfall (highly variable amount of rainfall), and long dry seasons (Murphy and Lugo 1986, Mooney et al. 1995). As of 2000, globally, TDF spanned 1,048,700 km² within the Americas, Africa, Eurasia, and Australasia (Miles et al. 2006). The hospitable climate and vegetation structure provides favorable conditions for human use including agriculture, forest product extraction, and livestock grazing (Murphy and Lugo 1986). Additional threats to TDFs include climate change, fire, forest fragmentation, and human population growth (Miles et al. 2006). TDF was estimated to cover 20% of global forest area in 2000; nearly 3% of that figure was removed by 2005 (Hansen et al. 2010). In Africa, a net annual loss of 0.34% occurred between 1990 and 2000 (Bodart et al. 2013) where 70-80% of all forest cover is defined as TDF (Murphy and Lugo 1986) and approximately half of the continent’s population resides and relies on its resources (Chidumayo and Gumbo 2010).

As a biodiversity hotspot (Myers et al. 2000), the forests of Madagascar are home to more than 90% of the island endemics (Dufils 2003) yet there has been a 40% loss in forest cover from 1950-2000 (Harper et al. 2007). Tropical dry forest in Madagascar is restricted to the western and southern-most regions of the island (Figure 1.1). It is particularly important as it represents the country’s highest plant endemism at 95% (Koechlin 1972), and it is experiencing a higher rate of deforestation than that of Malagasy rainforests (Sussman and Rakotozafy 1994). The majority of the remaining TDF is disturbed to some degree, yet it supports some of Madagascar’s flagship species. Small forest patches in southern Madagascar may still be capable
of sustaining wildlife (Bodin et al. 2006) since the collective area of suitable habitat patches in close proximity to one another may remain functional to certain species (Andrén 1994).

Conservation scientists in Madagascar have historically concentrated their efforts on large, intact habitats with little human disturbance; the conservation value of small and/or disturbed areas has been comparatively overlooked (Bodin et al. 2006). Given that the large majority of forests in Madagascar are used by humans for multiple activities, it follows that there should be a means to identify those forests with the greatest conservation potential.

Livestock grazing is one of the main disturbances in the southern TDF of Madagascar as livestock represent the primary source of income for much of the local population (Sussman et al. 1994). Human disturbances in Malagasy forests have had negative impacts on wildlife species resulting in overall reduced species diversity, although these impacts vary by importance, ecoregions, and even among related species (Irwin et al. 2010).

The TDF of southern Madagascar consists of multiple distinct forest classes including gallery, dry deciduous, and spiny thicket. The high variability of vegetation composition, structure, and climate within each forest class of the TDF (Murphy and Lugo 1986) could result in variable flora and fauna response to disturbances. Some TDF classes may be more or less affected by disturbances such as grazing.

A forest with high conservation value exhibits: high biodiversity (threatened, endangered, or endemic species); large landscape-level forest with viable populations of naturally occurring species, threatened or endangered ecosystems; basic ecosystem services (fundamental to needs of local communities); and/or critical to local culture (Seghedin 2011). The TDF of southern Madagascar meets multiple of these criteria for high conservation value, necessitating suitable management of human related disturbances.
Figure 1.1 Land cover map of Madagascar (modified from DuPuy and Moat 1996)

Study Area

Research was conducted at the Beza Mahafaly Special Reserve (-23.6505, 44.631931) located in south-west Madagascar, 35 kilometers NE of Betoiky. The site was established in 1978 as a joint conservation project between the local community and the Agronomy Sciences Department at the University of Antananarivo; in 1986 it was designated as a Special Reserve (Ratsirarson 2003). The site is highly seasonal with distinct wet (November to March) and dry
(April to October) seasons. Three classes of TDF are found within the reserve: gallery, dry deciduous, and spiny thicket. These classes are arranged by distance to water, with gallery found closest to the water, followed by dry deciduous further away, and finally spiny thicket at the furthest distance from water.

The reserve consists of two main discontiguous parcels with additional lands that were added in a recent reserve extension (Figure 1.2). Parcel 1 is roughly 80 ha consisting of gallery and dry deciduous forest. It is surrounded by a fence that has prevented livestock grazing within the parcel since its installation in 1979 (Richard et al. 1988). Grazing is unrestricted within parcel 2 (600 ha) and the extension, creating a mixture of moderately to heavily grazed areas outside of parcel 1.

![Figure 1.2 Map of the Beza Mahafaly Special Reserve with study area in gray and reference to location in Madagascar.](image)
To measure the effects of grazing within TDF at Beza Mahafaly, 24 sampling sites were established within two dry forest classes (gallery and dry deciduous) and three levels of grazing intensity (ungrazed, moderately, and heavily grazed) (Figure 1.3). Spiny thicket was not used in this study due to the lack of an ungrazed control area for this class. Forest class was established via a land cover classification from multi-temporal satellite imagery of the study area (Axel 2010). Grazing intensity was determined from multi-year global positioning system (GPS) tracking data of the two largest livestock herds within the reserve as well as from local knowledge of grazing history. Areas that experienced grazing every year were classified as heavily grazed, while areas that experienced inconsistent grazing were classified as moderately grazed.

Figure 1.3 Map of sampling sites established within the study area at the Beza Mahafaly Special Reserve. The black outline denotes the fence surrounding Parcel 1, containing the ungrazed sampling sites within.
This resulted in six distinct sampling categories: gallery forest ungrazed, gallery forest moderately grazed, gallery forest heavily grazed, dry deciduous forest ungrazed, dry deciduous forest moderately grazed, and dry deciduous forest heavily grazed. Discernible structural differences can be seen in the canopy and understory structure of each category (Figure 1.4). Moving from ungrazed to heavily grazed gallery forest results in decreased canopy cover and overgrown understory. Moving from ungrazed to heavily grazed dry deciduous forest results in decreased canopy cover and presence of bare open soil patches.

**Sampling Design**

The purpose of this study was to assess the conservation value of grazed tropical dry forests through wildlife population, acoustic, and vegetation sampling. We used both direct and indirect sampling techniques to measure how grazing activity affects the structure and function of the TDF in southern Madagascar. While forests in this region are not typically cleared to create grasslands for grazing, the livestock still impact the forest structure. Systematic vegetation sampling of the canopy and understory through species diversity, richness, cover, and soil characteristics were measured at each of the twenty-four sampling sites (Chapter 2).

A land cover classification model of forest class and grazing intensity was built by combining spectral indices applied to satellite images with ground habitat data. The resulting Random Forest models were tested for accuracy in classification results and significance between classified groups (Chapter 3).

The two diurnal lemur species found within the southern TDF, the ring-tailed lemur (*Lemur catta*) and Verreaux’s sifaka (*Propithecus verreauxi*), were used as focal species for occupancy modeling. As flagship conservation species in the region (Durbin 1999), changes in
their populations due to human disturbances provides vital information to land managers.

Occupancy surveys of both species were conducted at all of the sampling sites in June and July 2014 to identify if and how forest class and grazing intensity affected occupancy and detection probabilities (Chapter 4).

The effects of grazing on the presence of other wildlife were remotely measured with the use of automated acoustic recorders. Acoustic sampling has been used as an inexpensive and non-invasive method to describe the structure of a community by comparing acoustic diversity in disturbed and undisturbed habitats. (Sueur et al. 2008). Recorders were installed at 12 of the sampling sites and programmed to record one minute soundscape samples every 15 minutes for 12 months. An acoustic index known as the normalized difference soundscape index—representing a ratio of biological to human-related sound activity—was calculated to detect significant differences in wildlife sound composition and activity (Chapter 5).
Figure 1.4 Habitat photos for each of the forest and grazing categories: gallery ungrazed (a), moderately grazed (b), heavily grazed (c), and dry deciduous ungrazed (d), moderately grazed (e), and heavily grazed (f).
Chapter 2

Measuring the effects of livestock grazing on canopy, understory, and species composition structure in a tropical dry forest of Madagascar

Introduction

As a biodiversity hotspot with high endemism, the tropical dry forest (TDF) of Madagascar is of particular conservation interest. Livestock grazing is the largest human impact affecting all forest classes (gallery forest, dry deciduous forest, and spiny thicket) within the TDF system in southern Madagascar. Understanding the effects of grazing on the forest structure and species composition is necessary for making suitable management decisions. The vast majority of the southern TDF is negatively affected by grazing, but some areas of grazed TDF are known to support populations of wildlife species such as tortoises, lemurs, and birds. Still others have been so damaged by grazing that wildlife population numbers are diminished or even absent.

Heavy grazing negatively affects plant biomass (Anderson et al. 2010), plant structural characteristics (Liang et al. 2009, Kraaij and Milton 2006), and plant species composition (Anderson and Hoffman 2007, Van der Westhuizen et al. 2005) within arid and semi-arid habitats. Grazing also directly impacts the soil through trampling, causing severe compaction and loss of ground cover (Su et al. 2006).

in a process known as ‘desertification’ (Ibrahim 1978). However, maintaining a moderate grazing regime could be used to maintain the structure and function of some systems (Lempesi et al. 2013, Papanastasis 2009, Ayyad and Elkadi 1982).

Species loss in the southern Madagascar TDF is of particular concern as livestock may consume plant species of interest (either endangered or endemic), especially in the dry season when agricultural fodder is limited. Grazing in other TDF systems has resulted in lower species diversity and decreased structural complexity (Stern et al. 2002). Grazing in the dry forests of Madagascar has shown mixed results in terms of species richness and diversity depending on forest type and soil conditions (Ratovonamana et al. 2013).

The goal of this study was to assess the effects of livestock grazing on the structure and composition of the southern TDF of Madagascar. The majority of the landscape is affected by humans, yet some areas are potentially useful conservation areas. These disturbed areas can support populations of wildlife valuable to Madagascar. By examining the vegetation characteristics of areas with different grazing intensity, my objective was to identify understory and canopy characteristics that are especially vulnerable to grazing disturbance. It was expected that both understory and canopy measurements would vary by forest class and grazing intensity. The ultimate goal was to identify a threshold level of grazing above which will support plant and wildlife species diversity and below which should be allowed to rest and recover. This information will help guide management strategies that allow some level of grazing so that the landscape can remain beneficial for both wildlife and human needs.
Methods

A grid of nine circular plots with radii of 10 m spaced 30 m apart was located at each of the twenty-four sampling sites selected as described in Chapter 1 (n=216) (Figure 2.1). Habitat variables sampled within each plot included: tree species richness (number of trees and vines greater than one meter in height); tree species diversity; number of kily (*Tamarindus indica*), a keystone species for *Lemur catta* (Jolly 1966, Sussman and Rakotozafy 1994, Sauther, 1998); total kily diameter at breast height (DBH, m); basal area (m²/ha); canopy height (m); and percent canopy cover. The tamarind tree, known locally as *kily*, is deciduous and a defining species of gallery forest (Jolly 1966, Sussman and Rakotozafy 1994). Basal area is the area of land occupied by the cross-section of tree trunks measured as the diameter at breast height (1.3 m). A wedge prism was used to calculate basal area by counting the number of trees larger than a set diameter threshold (Husch et al. 2003). The diameter threshold was determined by the prism factor or basal area factor (BAF), describing the angle of the prism. The number of trees that fell within the measurement were multiplied by the basal area factor (BAF 10) to determine basal area in m²/ha. To determine percent canopy cover, hemispherical photos were taken one meter above ground at the center of each plot with a Nikon Coolpix 990 digital camera and Nikon FC-E8 fisheye lens. Original color pixels from the photos were converted into black and white pixels to calculate a sine-weighted measure of canopy openness using the software program GLA (Gap Light Analyzer) (Fraze et al. 2000). The inverse of this measurement was assigned as canopy cover.

Three one square meter sub-plots were randomly placed within each circular plot (n=648) to measure understory characteristics including: seedling species richness (tree and vine species less than one meter in height/length), total number of seedlings, seedling species diversity,
percent seedling cover, soil hardness (pound force, lbf), leaf litter thickness (cm), and percent herbaceous cover. Soil hardness was determined by pressing a Lang Penetrometer (Lang Penetrometer, Inc.) into the soil and recording the force in pounds required to drive the probe into the soil. The Lang penetrometer has been used in another study in Madagascar to measure human impacts on soil (Zavada et al. 2009).

Resulting values for each habitat characteristic were power transformed to exhibit normality using the box-cox transformation (Box and Cox 1964). Tests of significance for difference in habitat characteristics by forest type were assessed using a two-way ANOVA. Tests of significance in vegetation parameters by grazing intensity were assessed as a six-way pairwise comparison using an ANOVA and Tukey’s HSD post-hoc test. Dissimilarities in tree and seedling species composition were visually analyzed using non-metric multidimensional scaling (NMDS) ordination plots of Euclidean distances between species compositions. All statistical analyses were conducted using the statistical software package R (R Core Team 2013).

Figure 2.1 Habitat plot sampling design.

**Results**

Nearly all habitat characteristics exhibited significant differences by forest class (Table 2.1). Tree species richness was not significantly different by forest class; however, seedling
Species richness was significantly higher in gallery forest than in dry deciduous. Mean tree basal area was significantly higher gallery forest than in dry deciduous, as was number of kily, canopy height, and percent canopy cover. In the understory, herbaceous cover, leaf litter thickness, seedling cover, and seedling number were all significantly higher in gallery forest. On the other hand, kily DBH and soil hardness were significantly higher in the dry deciduous forest.

Table 2.1 Mean and standard error of habitat characteristics by forest class. Means with different letters are significantly different (ANOVA, α=0.05).

<table>
<thead>
<tr>
<th>Canopy</th>
<th>Gallery</th>
<th>Dry deciduous</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest class</td>
<td>Tree richness</td>
<td>Basal area</td>
</tr>
<tr>
<td>Gallery</td>
<td>16.6 ± 3.7 a</td>
<td>8.5 ± 2.8 a</td>
</tr>
<tr>
<td>Dry deciduous</td>
<td>16.5 ± 4.1 a</td>
<td>6.2 ± 1.9 b</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Understory</th>
<th>Seedling richness</th>
<th>Seedling cover</th>
<th>Seedling number</th>
<th>Soil hardness</th>
<th>Leaf litter thickness</th>
<th>Herbaceous cover</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gallery</td>
<td>2.4 ± 1.3 a</td>
<td>22.9 ± 11.8 a</td>
<td>4.0 ± 2.4 a</td>
<td>9.5 ± 3.3 a</td>
<td>2.2 ± 1.1 a</td>
<td>44.9 ± 15.7 a</td>
</tr>
<tr>
<td>Dry deciduous</td>
<td>1.4 ± 0.8 b</td>
<td>17.2 ± 11.1 b</td>
<td>2.6 ± 2.2 b</td>
<td>13.2 ± 2.4 b</td>
<td>1.1 ± 0.8 b</td>
<td>37.9 ± 17.9 b</td>
</tr>
</tbody>
</table>

Species richness was highest in ungrazed dry deciduous forest and lowest in moderately grazed deciduous forest. While there was a difference in mean tree basal area differed by forest class; there was no with but no significant difference by grazing intensity within each class. Ungrazed dry deciduous forest had the highest number of kily among all dry deciduous forest, close to the high number of kily in the gallery forest. Percent canopy cover and canopy height were significantly lower in the grazed dry deciduous forest followed in increasing value by ungrazed dry deciduous, grazed gallery, and ungrazed gallery sites.

While mean seedling richness, cover, and number were significantly different by forest class, pairwise comparisons by grazing intensity showed similar means between grazed gallery and ungrazed dry deciduous forest. Soil hardness was significantly highest in the grazed dry
deciduous forest and lowest in the ungrazed gallery forest. Leaf litter thickness followed a similar pattern, with the lowest values in grazed dry deciduous forest and the highest in ungrazed gallery forest. Percent herbaceous cover had no relationship with forest class or grazing intensity.

Total number of tree and vine species greater than one meter in height detected during sampling equaled 125. Dissimilarity in tree species composition by forest class was evident in the NMDS plot (Figure 2.2), where 95% confidence bands surrounding the forest clusters indicated a significant difference between the two distinct forest classes (nonparametric PERMANOVA, p=0.001). There was less separability of species composition by grazing presence within each forest class (Figure 2.3). There was no discernible separation in species composition between grazed and ungrazed gallery forest, but there was some degree of separation in species composition between grazed and ungrazed dry deciduous forest (less separability of species composition was seen when species composition was plotted by grazing intensity within forest) (Figure 2.4).

Total number of seedlings (tree and vine species less than one meter in height) detected during sampling equaled 80. Dissimilarity in seedling species composition by forest class exhibits a similar trend in the tree species composition analysis with significant clustering by forest class (nonparametric PERMANOVA, p-value=0.001) (Figure 2.5). When divided by grazing presence and intensity, all categories within each forest class appear to have similar species compositions with no visible clustering among them (Figure 2.6 and 2.7).
Table 2.2 Mean and standard error of habitat characteristics by forest class and grazing intensity. Means with the same letters are not significantly different (Tukey’s HSD, α=0.05, pairwise comparison of 6 variables).

**Canopy**

<table>
<thead>
<tr>
<th>Forest class</th>
<th>Grazing intensity</th>
<th>Tree richness</th>
<th>Basal area</th>
<th>Number of kily</th>
<th>Kily DBH</th>
<th>Canopy cover</th>
<th>Canopy height</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gallery</td>
<td>Ungrazed</td>
<td>15.6 ± 3.6 b</td>
<td>8.4 ± 2.4 ab</td>
<td>4.0 ± 2.8 a</td>
<td>1.6 ± 0.8 ab</td>
<td>79.8 ± 4.8 a</td>
<td>17.8 ± 3.5 a</td>
</tr>
<tr>
<td></td>
<td>Moderately</td>
<td>17.6 ± 3.1 ab</td>
<td>9.1 ± 3.2 a</td>
<td>4.8 ± 4.2 a</td>
<td>2.1 ± 1.4 a</td>
<td>72.5 ± 10.1 b</td>
<td>17.9 ± 5.4 a</td>
</tr>
<tr>
<td></td>
<td>Heavily</td>
<td>16.7 ± 4.2 bc</td>
<td>7.9 ± 2.8 ab</td>
<td>3.8 ± 2.8 a</td>
<td>1.9 ± 1.1 ab</td>
<td>70.9 ± 7.8 b</td>
<td>14.0 ± 3.0 b</td>
</tr>
<tr>
<td>Dry deciduous</td>
<td>Ungrazed</td>
<td>20.0 ± 3.7 a</td>
<td>7.2 ± 1.9 bc</td>
<td>1.5 ± 2.7 b</td>
<td>1.1 ± 0.9 b</td>
<td>65.2 ± 6.1 c</td>
<td>11.7 ± 2.9 c</td>
</tr>
<tr>
<td></td>
<td>Moderately</td>
<td>13.9 ± 2.9 c</td>
<td>5.4 ± 1.7 d</td>
<td>0.2 ± 0.6 c</td>
<td>0.9 ± 0.4 b</td>
<td>54.0 ± 10.2 d</td>
<td>9.1 ± 2.5 d</td>
</tr>
<tr>
<td></td>
<td>Heavily</td>
<td>14.6 ± 3.4 c</td>
<td>6.0 ± 1.7 cd</td>
<td>0.3 ± 0.6 c</td>
<td>0.8 ± 0.3 b</td>
<td>57.8 ± 9.8 d</td>
<td>8.6 ± 1.8 d</td>
</tr>
</tbody>
</table>

**Understory**

<table>
<thead>
<tr>
<th>Forest class</th>
<th>Grazing intensity</th>
<th>Seedling richness</th>
<th>Seedling cover</th>
<th>Seedling number</th>
<th>Soil hardness</th>
<th>Leaf litter thickness</th>
<th>Herbaceous cover</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gallery</td>
<td>Ungrazed</td>
<td>2.9 ± 1.3 a</td>
<td>28.9 ± 12.4 a</td>
<td>4.9 ± 2.5 a</td>
<td>7.0 ± 2.0 d</td>
<td>2.8 ± 0.9 a</td>
<td>37.6 ± 16.4 b</td>
</tr>
<tr>
<td></td>
<td>Moderately</td>
<td>2.2 ± 1.2 ab</td>
<td>19.9 ± 9.9 b</td>
<td>3.4 ± 2.2 ab</td>
<td>9.8 ± 3.1 c</td>
<td>2.0 ± 1.1 b</td>
<td>52.1 ± 13.2 a</td>
</tr>
<tr>
<td></td>
<td>Heavily</td>
<td>2.0 ± 1.3 b</td>
<td>19.8 ± 10.9 bc</td>
<td>3.6 ± 2.4 ab</td>
<td>11.7 ± 2.8 b</td>
<td>1.7 ± 0.9 b</td>
<td>44.9 ± 14.2 ab</td>
</tr>
<tr>
<td>Dry deciduous</td>
<td>Ungrazed</td>
<td>1.7 ± 0.9 b</td>
<td>18.9 ± 10.8 bc</td>
<td>2.6 ± 1.4 bc</td>
<td>11.1 ± 1.8 bc</td>
<td>1.6 ± 0.8 b</td>
<td>41.1 ± 21.2 ab</td>
</tr>
<tr>
<td></td>
<td>Moderately</td>
<td>1.6 ± 0.9 bc</td>
<td>20.0 ± 11.5 b</td>
<td>3.4 ± 2.9 b</td>
<td>14.0 ± 2.0 a</td>
<td>0.8 ± 0.7 c</td>
<td>37.1 ± 15.2 b</td>
</tr>
<tr>
<td></td>
<td>Heavily</td>
<td>1.0 ± 0.6 c</td>
<td>12.8 ± 9.9 c</td>
<td>1.9 ± 1.9 c</td>
<td>14.4 ± 1.9 a</td>
<td>0.8 ± 0.5 c</td>
<td>35.6 ± 16.8 b</td>
</tr>
</tbody>
</table>
Figure 2.2 Non-metric multidimensional scaling plot of tree species composition by forest class. Ellipses indicate a 95% confidence band for each cluster.
Figure 2.3 Non-metric multidimensional scaling plot of tree species composition by forest class and grazing presence.
Figure 2.4 Non-metric multidimensional scaling plot of tree species composition by forest class and grazing intensity.
Figure 2.5 Non-metric multidimensional scaling plot of seedling species composition by forest class. Ellipses indicate a 95% confidence band for each cluster.
Figure 2.6 Non-metric multidimensional scaling plot of seedling species composition by forest class and grazing presence.
Figure 2.7 Non-metric multidimensional scaling plot of seedling species composition by forest class and grazing intensity.
Discussion

The significant differences of most habitat characteristics by forest class support the initial assumption that the two classes used in this study are distinctive habitats within the TDF system. This is especially evident in variables relating to forest structure and canopy. Even in such a small study area, differences in soil and microclimate between the gallery and dry deciduous forests have been documented (Sussman and Rakotozafy 1994). Gallery forest is a truly distinct forest class facing different risks, as it contains species such as the *kily* that provide fodder for livestock during the long dry season. Its position as a dry forest class near water places it at risk of clearing for agriculture in this prime irrigated area. The unique risks associated with this class could necessitate a different management regime from the dry deciduous forest class.

While there are differences in the understory between the ungrazed gallery and dry deciduous forest, grazing activities appear to alter the forest in ways that make the understory of their grazed counterparts more homogeneous with one another. Overgrazing in a range of forest habitats has resulted in similar conclusions, regarding the species diversity and structure of understories (Gillespie et al. 2000, Dale et al. 2002, Onaïndia et al. 2004).

Grazing activities in both forest classes resulted in more open canopies and lower canopy height. In the gallery forest, this is most likely due to the routine chopping of branches from the canopy of large trees (especially *kily*) to provide fodder to livestock during the long dry season when most of the edible understory has been depleted (Figure 2.8a). In the dry deciduous forest, more open and shorter canopy in grazed forests is most likely due to a concomitant reduction of tree basal area and number of *kily* in grazed forest sites. Tree species used for livestock fodder in the dry deciduous forest are small stemmed; cut at about 1 meter for tree canopies to fall to the ground where cattle can easily feed on the leaves (Figure 2.8b). As reported elsewhere (Jolly
1966), *kily* are a characteristic species of gallery forest, and while this species can be found in dry deciduous forest, it is found in much higher numbers in the gallery. This can be largely explained by differences in soil substrate (i.e., soil hardness) and microclimate of both classes.

Surprisingly, grazing had little effect on the number of *kily* in gallery forest, suggesting that for now, the continued practice of coppicing *kily* has not resulted in *kily* death. However, there was a marked difference in the number of *kily* between grazed and ungrazed dry deciduous forest sites. This is troubling, given the small number of *kily* present in the dry deciduous forest. While *kily* do not represent a large sample of trees in the dry deciduous forest, the fruit of the *kily* is a keystone resource for *Lemur catta* and a particularly important food resource during the dry season (Sauther 1998). The loss of *kily* trees represents a significant loss to *L. catta*, *Propithecus verreauxi*, mouse lemur, as well as birds and humans. The reduction in *kily* in grazed dry
deciduous forest may be due to two factors. First, with the opening of the canopy and increased trampling, seedling recruitment may be reduced, resulting in fewer adults. Two, adult kily may experience microclimate conditions that are unfavorable for growth, or unfavorable to healing after coppicing which results in the death of adult trees. This is a question that should be investigated further.

The higher seedling richness, seedling cover, and seedling number observed in the gallery forest could be due to inherent differences in the forest classes while grazing presence had a negative effect on both forests. Grazing is known to negatively affect seedling survival and growth (Teich et al. 2005, Giorgis et al. 2009) and this may explain lower seedling richness, seedling cover, and seedling number across both forest classes.

When assessing the heavily grazed dry deciduous forest in particular, the significantly lower means of measured seedling characteristics implies that this class could be more sensitive to grazing impacts. This decreased seedling condition in the heavily grazed dry deciduous is not surprising given a similar pattern depicted in soil compaction and leaf litter thickness. Livestock trampling causes severe compaction and a decrease in ground cover (Su et al. 2006), leading to erosion and a loss of fertile top soil on bare ground (Kumbasli et al. 2010). Top soil loss combined with high compaction is not suitable conditions for germination and seedling survival. While increased presence of livestock results in higher seed dispersal (Janzen 1984), young plants are unlikely not survive to adulthood. The seedlings may well germinate in the livestock scat but their root systems may be less likely to establish in the highly compacted soil without the benefit of nutrients from leaf litter. The open canopy would also expose seedlings to high sunlight possibly leading to desiccation.
The significant clustering of tree and seedling species compositions by forest class further supports the distinction of two separate forest classes. The clustering of ungrazed sites separate from grazed sites in the dry deciduous forest and not in the gallery forest demonstrates how each forest responds differently to disturbances. Differences in canopy composition of the dry deciduous forest could result from herders selectively choosing which adult plants to coppice when providing livestock fodder in the long dry season. The lack of seedling composition clusters by grazing intensity in both forest classes indicates less of an effect from grazing on seedling communities. Unlike herders deciding which species to cut, livestock do not appear selective in their consumption or trampling of the understory.

There is a distinct difference in structure and composition between the gallery and dry deciduous forest classes within the TDF of southern Madagascar. Grazing pressure affects the canopy, understory structure, and overall species composition of each class differently. Understanding each characteristics response to disturbances has important implications for land management, where strategies aimed at targeting species of interest could benefit from this knowledge. Moderately disturbed areas could exhibit characteristics suitable to sustain the species of interest in areas that may be discounted in traditional conservation strategies that focus on large areas of so-called pristine habitat.
Chapter 3

Assessment of a random forest classifier in a grazed tropical dry forest of Madagascar

Introduction


Two types of image classification are widely used: supervised and unsupervised. Supervised classification requires the user to define multiple land cover training samples that are used to classify the remaining image through software analysis. This method can be highly accurate but time consuming and heavily reliant on the user’s knowledge of the landscape. In unsupervised classification, image software programs use statistical clustering to define a set number of classes without training knowledge from the user. This method is fast and relatively easy to implement, although it is highly sensitive to the assigned number of classes and a user’s prior knowledge of the landscape is not used. One popular method in unsupervised classification is known as ISODATA, which relies on computer algorithms to assign clusters. Supervised classifications most often used include: Maximum likelihood, Mahalanobis Distance, and Minimum Distance methods.
Classification trees, or decision trees, are reliable in classifying land cover from satellite imagery (Hansen et al. 1996, Friedl and Brodley 1997, DeFries et al. 1998, Hansen et al. 2000), and are often found to be the most accurate classification method in some landscapes (Friedl and Brodley 1997, Pal and Mathers 2003). One such ensemble decision tree method, known as a Random Forests (RF) classification algorithm (Breiman 2001), has been widely used for land cover classifications (Pal 2005, Gislason et al. 2006, Chan and Paelinckx 2008, Na et al. 2010, Hayes et al. 2014). Implementation of some classification tree classifiers can be difficult in traditional remote sensing packages (i.e. ERDAS Imagine, IDRISI Selva), but the statistical package R is powerful enough to perform the analysis on large raster data sets.

A RF model builds hundreds of decision trees with a specified number of nodes from a random collection of input variables. Random subsets of data (or pixels in the case of satellite image classification) are run through the trees and classified by each tree. The final classification of the pixel is based on the majority “vote” of each of the trees. A subset of the data are held back to allow for accuracy assessment. Random forest classification is highly accurate while handling large datasets, missing data, and correlated variables (Cutler et al. 2007).

Image classifications primarily focus on assigning general land cover types (forest, urban, water) or forest types (deciduous, evergreen, etc.). Researchers can then observe change in these land cover classifications over time to estimate large-scale effects from disturbances such as fires (Langner et al. 2007, Stocks et al. 2002), hurricanes (Wang et al. 2010), floods (Profeti and Macintosh 1997, Sado and Islam 1997), and logging (Stone and Lefebvre 1998). Yet, there is little research on classifying forests by condition with respect to more subtle disturbances, such as livestock grazing.
The aim of this study was to build a RF model and assess its accuracy and potential in differentiating between grazing intensity in tropical dry forest. The RF model will be built using data combined from satellite image analysis and ground habitat sampling, as one of the benefits of RF modeling is the ability to incorporate both field collected variables with remotely sensed data. The resulting classification by forest and measure of disturbance will be used to create a land cover map of forest quality. Classifications will be assessed on how well the model correctly discriminated between levels of grazing in different forest classes. It was expected that combining satellite and ground sampled data would result in the highest classification accuracy of forest class and grazing intensity.

**Methods**

Research was conducted at the Beza Mahafaly Special Reserve in south west Madagascar. Twenty-four sampling sites (described in Chapter 1) located in two forest classes (gallery and dry deciduous) and three levels of grazing intensity (ungrazed, moderately grazed, and heavily grazed) were used in RF model building and analysis. Training data collected at these sampling sites included understory and canopy vegetation data (see Chapter 2). Habitat sampling variables included: tree richness, basal area, number of *kily* (deciduous tamarind tree characteristic of the gallery forest), *kily* diameter at breast height (dbh), percent canopy cover, canopy height, seedling richness, percent seedling cover, seedling number, soil hardness, leaf litter thickness, and percent herbaceous cover.

Two Landsat 8 images were selected for analysis: a January 26, 2014 image from the middle of the rainy season (November through March) and a July 2, 2014 image from the middle of the dry season (April through October) to capitalize on differences in vegetation seasonality.
Both images were pre-processed by converting to top of atmosphere reflectance followed by dark object subtraction.

Vegetation spectral indices were calculated from each Landsat image for inclusion as layers in the random forest model. The normalized difference vegetation index (NDVI) is one of the most used indices in land cover classifications (Ali et al. 2013, Rodrigues et al. 2013). In arid and semiarid landscapes with bare soil patches present, the modified soil adjusted vegetation index (MSAVI2) has been shown to measure greenness more accurately than NDVI (Qi et al. 1994). The Enhanced Vegetation Index (EVI, Waring et al. 2006) is used to enhance vegetation signal in response to canopy structure. It is successful at dealing with soil background and atmospheric aerosol influences in images (Liu and Heute 1995). The Enhanced Vegetation Index also displays a more dynamic range than NDVI (Heute et al. 2002), useful in the heterogeneous structure of the TDF. The modified triangular vegetation index (MTVI2) is a highly accurate predictor of green leaf area index (Haboudane et al. 2004). The moisture stress index (MSI) (Rock et al. 1985) can detect large scale disturbances based on moisture content. The normalized infrared index (NDII) has also been shown sensitive to moisture changes in the canopy (Hardisky et al. 1983) while the mid-infrared index (MIR12) (Solaimani et al. 2011) has been related to percent canopy cover.

Textural variation in the homogeneous canopy structure has been used to identify forest disturbances. Differences in canopy texture were measured here using a moving standard deviation index (MSDI) (Tanser and Palmer 2000) applied to the red, near infrared (NIR) and shortwave infrared (SWIR) bands.

All of the spectral indices above were calculated for both the July and January Landsat 8 images. These bands were then differenced by subtracting the July data from the January data to
display the variation between the extremes of the dry and wet seasons. Additional data included a digital elevation model (DEM), which is correlated with distance to water, a defining characteristic of the forest classes in the TDF. A layerstacked image was created from combining 40 layers including: January and July bands 2-7, MSDI (red, NIR, SWIR), vegetation indices (EVI, MIRI, MSAVI2, MSI, MTVI2, NDII, NDVI), image differenced vegetation indices, and DEM. Layers included in the final layerstack of images for the Random Forest model are defined in Table 3.1.

Table 3.1 List of spectral indices used in the satellite image analysis. Variables in the equations include the visible blue, green, and red bands, near infrared band (NIR), first shortwave infrared band (SWIR1), and pixel digital number (DN).

<table>
<thead>
<tr>
<th>Spectral Index</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>( \frac{NIR - RED}{NIR + RED} )</td>
</tr>
<tr>
<td>MSI</td>
<td>( \frac{SWIR1}{NIR} )</td>
</tr>
<tr>
<td>NDII</td>
<td>( \frac{NIR - SWIR1}{NIR + SWIR1} )</td>
</tr>
<tr>
<td>MIRI2</td>
<td>( \frac{SWIR1 - RED}{SWIR1 + RED} )</td>
</tr>
<tr>
<td>MSAVI2</td>
<td>( \frac{2 \times (NIR + 1) - \sqrt{(2 \times (NIR + 1) - 8 \times (NIR - RED))^2}}{2} )</td>
</tr>
<tr>
<td>EVI</td>
<td>( 2.5 \left( \frac{NIR - RED}{NIR + (6 \times RED) - (7.5 \times BLUE) + 1} \right) )</td>
</tr>
<tr>
<td>MTVI2</td>
<td>( \frac{1.8(NIR - GREEN) - 3.75(RED - GREEN)}{\sqrt{(2 \times NIR + 1)^2 - (6 \times NIR - 5 \times RED)^2 - 0.5}} )</td>
</tr>
<tr>
<td>MSDI</td>
<td>( \sqrt{\frac{\sum_{i=1}^{N}(DN_i - \bar{DN})^2}{N}} )</td>
</tr>
</tbody>
</table>
A grid of nine vegetation sampling plots with a radius of 10 meters spaced 30 meters apart was located at each of the 24 sampling sites. Ground habitat variables were sampled at each of these plots (described in Chapter 2). Pixel values were extracted from the center of each plot for every layer in the layerstack, resulting in a block of nine pixel values for each of the 24 sampling site. Pixels were treated as independent in the model due to the lack of evidence for spatial autocorrelation.

Two random forest models were built: one with image sampling variables combined with ground sampling variables (described Chapter 2) and one with satellite variables alone. Models were built and analyzed using the software program R (R Core Team 2013) with the randomForest package (Liaw and Wiener 2002). To ensure that the model reached convergence, 1000 trees were used to build each model.

Each RF model was used to create three land cover classification schemes of the study site: 1) forest class (gallery forest, dry deciduous forest, and non-forest); 2) forest class by grazing presence; and 3) forest class by grazing intensity (ungrazed, moderately grazed, and heavily grazed). A separate classification error rate was generated for each classification. Significance tests of land cover classes for each classification scheme were assessed using a nonparametric multivariate test (multiresponse permutation procedure - MRPP) (Mielke et al. 1976). Multidimensional scaling plots using RF proximities (Cutler et al. 2007) were used to graphically represent the separability of the classes in each classification scheme. Finally, land cover classifications were mapped in ArcGIS 10.0 (Environmental Systems Research Incorporated).
Results

Classification by forest class resulted in an error rate around 5% for both RF models (Table 3.2). Classification by forest class and grazing presence resulted in a higher error rate of about 13% for both RF models with the dry deciduous ungrazed category having the highest error rate of 28% for both (Table 3.3). Classification by forest class and grazing intensity resulted in the highest error rate of 22% with both grazed gallery and ungrazed dry deciduous categories having the highest error rates from 22-50% (Table 3.4). Classification error rates varied little between the satellite plus habitat variable model and the satellite-only model.

Table 3.2 Classification error rates by forest class for two RF models: combining habitat and satellite variables together and using only satellite variables.

<table>
<thead>
<tr>
<th>Forest class</th>
<th>Habitat and satellite RF model</th>
<th>Satellite RF model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gallery</td>
<td>5.56%</td>
<td>4.63%</td>
</tr>
<tr>
<td>Dry deciduous</td>
<td>4.63%</td>
<td>4.63%</td>
</tr>
<tr>
<td>Total</td>
<td>5.09%</td>
<td>4.63%</td>
</tr>
</tbody>
</table>

Table 3.3 Classification error rates by forest class and grazing presence for two RF models: combining habitat and satellite variables together and using only satellite variables.

<table>
<thead>
<tr>
<th>Forest class and grazing presence</th>
<th>Habitat and satellite RF model</th>
<th>Satellite RF model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gallery ungrazed</td>
<td>13.89%</td>
<td>13.89%</td>
</tr>
<tr>
<td>Gallery grazed</td>
<td>12.50%</td>
<td>15.28%</td>
</tr>
<tr>
<td>Dry deciduous ungrazed</td>
<td>27.78%</td>
<td>27.78%</td>
</tr>
<tr>
<td>Dry deciduous grazed</td>
<td>4.17%</td>
<td>4.17%</td>
</tr>
<tr>
<td>Total</td>
<td>12.50%</td>
<td>13.43%</td>
</tr>
</tbody>
</table>

Table 3.4 Classification error rates by forest class and grazing intensity for two RF models: combining habitat and satellite variables together and using only satellite variables.

<table>
<thead>
<tr>
<th>Forest class and grazing intensity</th>
<th>Habitat and satellite RF model</th>
<th>Satellite RF model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gallery ungrazed</td>
<td>2.78%</td>
<td>8.33%</td>
</tr>
<tr>
<td>Gallery moderately grazed</td>
<td>50.00%</td>
<td>50.00%</td>
</tr>
<tr>
<td>Gallery heavily grazed</td>
<td>22.22%</td>
<td>22.22%</td>
</tr>
<tr>
<td>Dry deciduous ungrazed</td>
<td>25.00%</td>
<td>25.00%</td>
</tr>
<tr>
<td>Dry deciduous moderately grazed</td>
<td>19.44%</td>
<td>19.44%</td>
</tr>
<tr>
<td>Dry deciduous heavily grazed</td>
<td>11.11%</td>
<td>11.11%</td>
</tr>
<tr>
<td>Total</td>
<td>21.76%</td>
<td>22.69%</td>
</tr>
</tbody>
</table>
Variables of most importance in both RF models and three classification schemes were all variables derived from satellite image analysis. Even when ground sampling variables were used, none were significant in the model classifications. When classifying by forest class for the habitat and satellite RF model, variables of most importance included: DEM, July NIR, NDVI difference, and July MSAVI2. Most important variables for the satellite-only model were January blue band, January green band, and DEM. When classifying by forest class and grazing presence for the habitat and satellite RF model, variables of most importance included: DEM, January SWIR1 MSDI, January MSI, July EVI, and January NDII. Most important variables for the satellite-only model were DEM, January green band, January SWIR1 MSDI, and January MSI. When classifying by forest class and grazing intensity for the habitat and satellite RF model, variables of most importance included: January SWIR1 MSDI, January MSI, and DEM. Most important variables for the satellite-only model were January SWIR1 MSDI, DEM, and January MSI. Given little difference between the two RF models, I selected the most parsimonious model which is the satellite-only model as illustrated in Figures 3.1, 3.2, and 3.3.
Figure 3.1 Land cover classification by forest class.
Figure 3.2 Land cover classification by forest class and grazing presence.
Figure 3.3 Land cover classification by forest class and grazing intensity
Significance testing with an MRPP was used to determine if considerable differences existed in the multivariate composition of variables in each classification of the satellite-only RF model. The MRPP resulted in statistical significance in the forest classification scheme (p-value=0.001) and forest class plus grazing presence classification scheme (gallery p-value=0.046, dry deciduous p-value=0.008) (Table 3.5). For the forest class plus grazing intensity classification scheme, significance was found when comparing gallery grazing categories (p-value=0.036), and dry deciduous grazing categories (p-value=0.002) but not in every pairwise comparison within both forest classes.

Table 3.5 Multiresponse permutation procedure (MRPP) pairwise results for three classifications using the satellite RF model: forest class, forest class plus grazing presence, and forest class plus grazing intensity. * denotes significant difference, $\alpha=0.05$.

<table>
<thead>
<tr>
<th>Classification</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest class</td>
<td></td>
</tr>
<tr>
<td>Gallery vs. dry deciduous</td>
<td>0.001 *</td>
</tr>
<tr>
<td>Forest class and grazing presence</td>
<td></td>
</tr>
<tr>
<td>Gallery grazed vs. gallery ungrazed</td>
<td>0.046 *</td>
</tr>
<tr>
<td>Dry grazed vs. dry ungrazed</td>
<td>0.008 *</td>
</tr>
<tr>
<td>Forest class and grazing intensity</td>
<td></td>
</tr>
<tr>
<td>Gallery all categories</td>
<td>0.036 *</td>
</tr>
<tr>
<td>Gallery ungrazed vs. moderately grazed</td>
<td>0.185</td>
</tr>
<tr>
<td>Gallery ungrazed vs. heavily grazed</td>
<td>0.027 *</td>
</tr>
<tr>
<td>Gallery moderately grazed vs. heavily grazed</td>
<td>0.213</td>
</tr>
<tr>
<td>Dry deciduous all categories</td>
<td>0.002 *</td>
</tr>
<tr>
<td>Dry ungrazed vs. moderately grazed</td>
<td>0.003 *</td>
</tr>
<tr>
<td>Dry ungrazed vs. heavily grazed</td>
<td>0.016 *</td>
</tr>
<tr>
<td>Dry moderately grazed vs. heavily grazed</td>
<td>0.185</td>
</tr>
</tbody>
</table>
Multidimensional scaling plots resulting from each classification scheme in the satellite-only RF model illustrate how clearly forest classes are separated in their respective classification schemes. Classification by forest (Figure 3.4) and forest plus grazing presence (Figure 3.5) resulted in clear separation or clustering of sites in the same category. Classification by forest class and grazing intensity (Figure 3.6) resulted in a plot with overlapping forest classes in different categories. Clustering of sites in the same classification group was only noticeable in the extreme ends of the plots: not forest, gallery ungrazed, and dry deciduous moderately grazed. Grazed gallery forest was overlapping with ungrazed dry deciduous forest and heavily grazed dry deciduous forest with not forest.

![Figure 3.4 Multidimensional scaling plot of classification by forest class.](image-url)
Figure 3.5 Multidimensional scaling plot of classification by forest class and grazing presence.

Figure 3.6 Multidimensional scaling plot of classification by forest class and grazing intensity.
Discussion

Given that the heterogeneity of the TDF makes it particularly difficult to classify, the RF models performed exceptionally well in classifying by forest class. The low error rates resulting from this study are comparable to the accuracy results of another RF model measuring disturbances in eastern Madagascar (Grinand et al. 2013).

The RF classification by grazing presence and by grazing intensity did not perform as well, but error rates were well within the range of what others report for classification by cover type. High error rate when classifying forest and grazing intensity appears to be due to the difficulty in distinguishing between grazed gallery and ungrazed dry deciduous forest. Ungrazed dry deciduous forest is spectrally similar to grazed gallery forest. Grazing in the gallery forest resulted in decreased canopy cover and increased species richness (see Chapter 2), traits common in the dry deciduous forest and detectable by satellite imagery. The boundary between ungrazed gallery and ungrazed dry deciduous forest within Parcel 1 is classified as grazed gallery forest even though all of this area has been ungrazed since 1978. This area classified as grazed gallery forest should most likely be classified as ungrazed dry deciduous. Future studies are needed to find or build other spectral indices that will be able to differentiate between disturbed gallery forest and undisturbed dry deciduous forest.

Surprisingly, land cover classification using satellite data alone performed equally well as one that incorporated both understory and forest canopy field collected data, demonstrating that satellite data is as reliable as on the ground vegetation data in classifying this TDF system. Satellite variables were consistently selected as variables of most importance, reflecting the wealth of information provided in satellite imagery. The ability to use multiple spectral bands of varying wavelengths or combinations of bands in one of many established algorithms allows
researchers to discern unique landscape characteristics. Accurate classifications rely on the ability to distinguish different features in a landscape, which is easily achieved given the potential wealth of information drawn from satellite images.

As expected, many different spectral variables used in this study were of importance in model building. Each variable describes a different characteristic of the landscape, potentially useful in each classification scheme. The importance of the digital elevation model (DEM) for all classification schemes was not surprising given its high correlation with distance to water. The arrangement of forest classes within the TDF is dependent on distance to water with gallery found nearest to water, dry deciduous further out, and spiny thicket furthest away. As a measure of textural uniformity, the moving standard deviation index (MSDI) was expected to be important in identifying grazed forests, and it was indeed the top variable of importance in both grazing presence and grazing intensity classifications. The moisture stress index (MSI) also appears to be successful at identifying grazed forest as it was a variable of most importance in all of the grazing classification schemes.

Random Forest classification appears to be a highly efficient method for land cover classification in the TDF, going beyond forest class to also reliably determine forest condition in terms of grazing presence or absence. The ability to remotely identify patches of specific habitat quality could be useful in conservation planning. In Madagascar, where there are multiple endangered taxa, RF models could be used to identify suitable habitat by species of interest. For instance, as ring-tailed lemurs (*Lemur catta*) are more likely to occupy ungrazed gallery forest (see Chapter 4) at higher densities (Axel and Maurer 2011), conservation planners could identify patches of likely occupancy to concentrate management efforts for the lemur’s benefit. Mapping disturbed but functioning patches of forest could also be used to maintain connectivity between
more suitable habitats. Methods that use the continuously evolving satellite image analyses in classifications are useful tools for guiding conservation management strategies.
Chapter 4

Estimating ring-tailed lemur (*Lemur catta*) and Verreaux’s sifaka (*Propithecus verreauxi*) occupancy in grazed tropical dry forests of southern Madagascar

Introduction

As a biodiversity hotspot (Myers et al. 2000) undergoing forest loss, Madagascar is at risk of losing species in multiple taxa (Brooks et al. 2002) including lemurs, one of Madagascar’s flagship conservation taxa (Durbin 1999). According to the IUCN Red-List, 90% of the 103 extant lemur species and subspecies are threatened to some degree. Habitat loss is the main threat to lemur survival, documented in all forest types throughout the island (Harper et al. 2007). Humans degrade lemur habitat for multiple uses, including agriculture, livestock grazing, and logging.

The southern tropical dry forests of Madagascar are dominated by two diurnal lemur species, the ring-tailed lemur (*Lemur catta*) and Verreaux’s sifaka (*Propithecus verreauxi*), whose ranges are predominately located in the country’s southern region (Mittermeier et al. 2006). *Lemur catta* and *P. verreauxi* live in female-dominated groups with both intra- and inter-species overlapping home ranges (Jolly 1966, Richard 1978, Sussman 1991). *Lemur catta* diet consists of fruits, leaves, herbs, and flowers (Sauther et al. 1999), while *P. verreauxi* consumes a mostly folivorous diet (Richard 1978, Simmen et al. 2003, Yamashita 2002). Both species spend time in the understory feeding on herbs and shrubs.

The tropical dry forest of Madagascar is highly seasonal, with a short wet period characterized by variable rainfall followed by a long dry period (Dewar and Wallis 1999). The extreme seasonality of this region, not only results in varied food resource use by the lemurs, but
also by the livestock who depend on forest resources during the dry season. During the rainy season, the availability of *L. catta* food resources (fruit, flowers, and especially leaves) is high, while in the dry season the availability of these resources drops dramatically (Sauther 1998) and it relies heavily on the fruit of *Tamarindus indica*, a deciduous tamarind tree (Simmen et al. 2006). While *P. verreauxi* is mostly folivorous, there is variability in feeding habits by season with fruit consumption dominating other resources during the rainy season and leaf consumption dominating in the dry season (Norscia et al. 2006).

Livestock grazing represents the largest forest disturbance in this region (Sussman et al. 1994). During the long dry season, herders bring their livestock to the forest to consume forest vegetation when their agricultural fodder is depleted. Livestock feed on understory vegetation and large tree branches cut from the canopy by herders. There is direct competition between the lemurs and livestock in both the understory and canopy.

While both lemur species share similar habit, *L. catta* abundance is notably higher in the gallery forest while *P. verreauxi* abundance is higher in the gallery forest, but not drastically different from abundance in the dry deciduous forest (Axel and Maurer 2011). In addition, each may respond differently to forest disturbance such as grazing intensity. Previous studies at Beza Mahafaly have shown *L. catta* to have higher densities in the gallery forest compared to the dry deciduous forest (Axel and Maurer 2011); they also have higher densities in protected ungrazed forest (Parcel 1) than in some unprotected and grazed forests (outside Parcel 1) (Gould et al. 2003, Axel and Maurer 2011). Previous studies on *P. verreauxi* at Beza Mahafaly have demonstrated higher densities in some grazed gallery forest than in some grazed dry deciduous forest (Axel and Maurer 2011). Variable responses to grazing were seen in the different forest classes with higher densities of *P. verreauxi* seen in ungrazed dry deciduous forest yet lower
densities of *P. verreauxi* in ungrazed gallery forest (Axel and Maurer 2011). At other study sites of TDF in southern Madagascar, higher densities were observed in gallery forest compared to dry deciduous forest for both *L. catta* (Jolly et al. 2002) as well as *P. verreauxi* (Norscia and Palagi 2008).

The goal of this study was to determine if *L. catta* and *P. verreauxi* occupancy was affected by forest classes and grazing intensity. Methods typically used to sample primates in forests rely on quadrat census and line-transect distance sampling. Unlike these methods, occupancy models use detection/non-detection and covariate data to estimate species occurrence across all sites, even when individuals are not detected (MacKenzie et al. 2002).

In this study, I used occupancy models to examine how *L. catta* and *P. verreauxi* detection and occupancy probabilities vary by habitat and sampling characteristics. This approach can account for sampling in different seasons and/or site variable covariates may have changed making this method highly repeatable (MacKenzie et al. 2002). Future researchers can resample the area and directly compare changes in occupancy probabilities and not rely on densities that can be difficult to compare over larger time periods.

Occupancy modeling has been used to assess species status, identify suitable habitat, and guide restoration and conservation activities (Peterman et al. 2012). It is an accurate and rapid method of habitat assessment for conservation (DeWan et al. 2009). Site occupancy models are used to estimate occupancy while allowing for imperfect detection probability (MacKenzie et al. 2002). Naïve estimates using presence/absence alone do not account for lower detection probabilities, and thus can underestimate occupancy estimates (Nichols et al. 1998, MacKenzie et al. 2006) and overestimate the importance of detection and occupancy covariates (Bailey et al. 2004, MacKenzie 2006). Site occupancy modeling accurately evaluates the effects of site and
sampling covariates allowing researchers to confidently compare detection and occupancy by variables of interest.

This purpose of this study was to examine the effects of grazing pressures on *L. catta* and *P. verreauxi* occurrence in a managed tropical dry forest in southern Madagascar. Effects of grazing on both species should be reflected in lemur occupancy probabilities within forests of varying grazing intensity. As both lemur species and livestock share similar food resources, I expected to detect a negative relationship between grazing intensity and occupancy. Given the differences in species composition between forest classes (see Chapter 2), lemur occupancy and detection were also expected to vary by forest class. In a threatened habitat such as the tropical dry forest of Madagascar, inexpensive and efficient occupancy estimates could provide vital information to aid in management decisions, conservation planning, and establishing monitoring regimes.

**Methods**

Occupancy sampling of *L. catta* and *P. verreauxi* was conducted at Beza Mahafaly Special Reserve from June to July 2014. Each of the twenty-four sampling sites (described in Chapter 1) were surveyed on ten occasions, where I noted presence or absence of both species. During each survey, observers relied on visual and audible signals for detection within 80 meters of the site center over a ten minute period. Surveys were conducted in the mornings between 8:00-11:30am and afternoons between 2:00-4:00pm when both species are active (Jolly 1966, Erkert and Kappeler 2004).

Presence/absence data were used to model occupancy and detection for each species as a function of habitat and sampling covariates. Habitat covariates included: forest class (gallery and
dry deciduous), grazing intensity (ungrazed, moderately grazed, and heavily grazed), and percent
canopy cover. Sampling covariates included: time of survey and presence of wind (Table 4.1).
Presence/absence of wind was recorded as this was thought to possibly affect detection of
vocalizations and/or movement in the canopy. Observers also noted detection by sight or sound
and lemur position in the forest (in the canopy or on the ground) at the time of detection.

Models with varying covariate combinations were analyzed for best fit and significance.
Forest class, grazing intensity, and canopy cover were tested as covariates of occupancy
probability (ψ) with forest class, wind, time, and time$^2$ as covariates of detection probability (p)
(Table 4.1). Given that canopy cover was found to be significantly related to forest class and to
grazing presence categories (dry deciduous grazed and ungrazed, gallery grazed and ungrazed)
(see Chapter 2) (Figure 4.1), it was used as a covariate to infer information about forest and
grazing presence. Seeing as canopy cover is correlated with forest and grazing intensity, these
covariates were not combined in the same model. Quadratic time (time$^2$) was used to determine if
detection probability was associated with the mean survey time (11:00am). Continuous
covariates (i.e., canopy cover, time, and time$^2$) were z-standardized before model testing.

Occupancy modeling was conducted in the software program R (R Core Team 2013)
with package R2WinBUGS (Sturtz et al. 2005) as an interface between R and the Bayesian
software program WinBUGS (Gilks et al. 1994, Lunn et al. 2009). A logit link Bayesian analysis
was used to estimate posterior distribution by combining prior covariate distributions with data
collected, leading to increased precision (McCarthy and Masters 2005). As opposed to
frequentist methods, Bayesian inference is unaffected by small sample size and provides more
intuitive results. The results of Bayesian analysis are more direct, estimating the probability of
obtaining a certain value as opposed to the probability of obtaining a specific data set.
Baye’s rule is the basis of Bayesian analysis and is used to derive the posterior distribution $p(\theta|x)$ or the probability of the parameters $\theta$ given the data $x$:

$$p(\theta|x) = \frac{p(x|\theta)p(\theta)}{p(x)}$$

where $p(x|\theta)$ is the maximum likelihood function for the observed data $x$, $p(\theta)$ is the prior distribution of parameters, and $p(x)$ is a normalizing constant or probability of obtaining the observed data $x$. A Markov Chain Monte Carlo (MCMC) simulation draws samples from the posterior distribution using sequences of random variables (Hastings 1970). A series of chains (collection of random variables conditionally independent of previous variables) with different initial values are drawn over multiple iterations until all chains converge, or until the distribution is conditional on all the parameters being modeled. Initial draws before convergence are then discarded from the distribution sample. Convergence is confirmed 1) visually, by observing plots of all chains and 2) mathematically, by calculating the Gelman Rubin statistic (Gelman et al. 2004), known as Rhat in WinBUGS where values close to one indicate convergence. To analyze each occupancy model, an MCMC simulation was run with three chains constructed over 2000 iterations with the first 500 discarded to ensure convergence.

Two modeling situations were run for each species, using non-informative and informative prior distributions of covariates. Non-informative or flat priors were assigned a normal distribution with a mean of zero and standard deviation of one. Informative priors for forest class and grazing presence were assigned from a 2010 occupancy study for both species at the same study area (Table 4.2).

Top performing models were denoted by low deviance information criterion (DIC) values (Spiegelhalter et al. 2002), with the best models assumed to have a $\Delta$DIC < 5. Only top models with significant covariates (95% credible interval (CRI) of covariate beta distribution did not
overlap with zero) were used to estimate occupancy and detection probability. A posterior predictive check determined goodness-of-fit with a Bayesian p-value, ranging from 0 to 1. Models of good fit have a p-value of 0.5 while those with a p-value approaching 0 or 1 are not considered to be good models. Significant model covariates were graphed by occupancy and detection probability.

Table 4.1 List of covariates with variable and data descriptions.

<table>
<thead>
<tr>
<th>Covariate name</th>
<th>Variable description</th>
<th>Data description</th>
</tr>
</thead>
<tbody>
<tr>
<td>forest</td>
<td>forest class</td>
<td>Categorical: 0=dry deciduous, 1=gallery</td>
</tr>
<tr>
<td>graze</td>
<td>grazing presence</td>
<td>Categorical: 0=ungrazed, 1=grazed</td>
</tr>
<tr>
<td>mod</td>
<td>moderate grazing</td>
<td>Categorical: 0=not moderately grazed, 1=moderately grazed</td>
</tr>
<tr>
<td>high</td>
<td>heavy grazing</td>
<td>Categorical: 0=not heavily grazed, 1=heavily grazed</td>
</tr>
<tr>
<td>canopy</td>
<td>percent canopy cover</td>
<td>Continuous</td>
</tr>
<tr>
<td>wind</td>
<td>wind presence</td>
<td>Categorical: 0=no wind present, 1=wind present</td>
</tr>
<tr>
<td>time</td>
<td>time</td>
<td>Continuous</td>
</tr>
<tr>
<td>time²</td>
<td>quadratic time</td>
<td>Continuous</td>
</tr>
</tbody>
</table>

Figure 4.1 Boxplot of percent canopy cover by forest and grazing categories.
Table 4.2 Prior beta distributions of forest class and grazing presence covariates for *L.catta* and *P. verreauxi* from a 2010 occupancy survey.

<table>
<thead>
<tr>
<th>Species</th>
<th>Covariate</th>
<th>Mean</th>
<th>SD</th>
<th>Covariate</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>L. catta</em></td>
<td>forest</td>
<td>1.5</td>
<td>0.7</td>
<td>forest</td>
<td>-0.7</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>graze</td>
<td>-0.2</td>
<td>0.7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>P. verreauxi</em></td>
<td>forest</td>
<td>0.6</td>
<td>0.7</td>
<td>forest</td>
<td>-0.4</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>graze</td>
<td>-0.3</td>
<td>0.8</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Results**

For *L. catta*, models of best fit (ΔDIC < 5) with the strongest covariates (95% CRI did not overlap with zero) included canopy cover as a covariate of occupancy probability with forest, time, and time² as covariates of detection probability (Tables 4.3 and 4.4). Using informative versus non-informative prior distributions for forest and grazing had little effect upon the resulting top models. Goodness-of-fit was confirmed for each model with p-values close to 0.5. As canopy cover increased, occupancy probability remained high between 0.85 and 0.95 with the credible interval narrowing as canopy cover increased (Figure 4.2). Detection probability was higher in the gallery forest compared to the dry deciduous forest with overlapping credible intervals (Figure 4.3). The additive effect of time and time² indicated that detection probability was highest in the early morning and late afternoon with the lower detection during the midday around 11:00am (Figure 4.4).
Table 4.3 Models of best fit (ΔDIC < 5) with strongest covariates (95% CRI of covariate beta distribution do not overlap with zero) of *L. catta* occupancy with non-informative priors (a) and informative priors (b). p(.) indicates detection probability kept constant.

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
<th>ΔDIC</th>
<th>Bayesian p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ψ(canopy) p(forest+time+time$^2$)</td>
<td>218.0</td>
<td>0.0</td>
<td>0.650</td>
</tr>
<tr>
<td>ψ(canopy) p(forest)</td>
<td>218.6</td>
<td>0.6</td>
<td>0.600</td>
</tr>
<tr>
<td>ψ(canopy) p(time+time$^2$)</td>
<td>219.7</td>
<td>1.7</td>
<td>0.556</td>
</tr>
<tr>
<td>ψ(canopy) p(.)</td>
<td>220.9</td>
<td>2.9</td>
<td>0.501</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
<th>ΔDIC</th>
<th>Bayesian p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ψ(canopy) p(forest+time+time$^2$)</td>
<td>217.6</td>
<td>0.0</td>
<td>0.638</td>
</tr>
<tr>
<td>ψ(canopy) p(time+time$^2$)</td>
<td>220.8</td>
<td>3.2</td>
<td>0.554</td>
</tr>
<tr>
<td>ψ(canopy) p(.)</td>
<td>220.9</td>
<td>3.3</td>
<td>0.518</td>
</tr>
</tbody>
</table>

Table 4.4 Beta estimates and standard deviation of covariates from best fit models of *L. catta* occupancy with non-informative priors (a) and informative priors (b).

<table>
<thead>
<tr>
<th>Model</th>
<th>ψ</th>
<th>p</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>forest</td>
<td>forest</td>
<td>time</td>
<td>time$^2$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ψ(canopy) p(forest+time+time$^2$)</td>
<td>1.4 ± 0.6</td>
<td>1.0 ± 0.4</td>
<td>-0.6 ± 0.3</td>
<td>0.5 ± 0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ψ(canopy) p(forest)</td>
<td>1.5 ± 0.5</td>
<td>0.9 ± 0.4</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ψ(canopy) p(time+time$^2$)</td>
<td>1.6 ± 0.5</td>
<td>-</td>
<td>-0.6 ± 0.3</td>
<td>0.5 ± 0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ψ(canopy) p(.)</td>
<td>1.6 ± 0.6</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>ψ</th>
<th>p</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>forest</td>
<td>forest</td>
<td>time</td>
<td>time$^2$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ψ(canopy) p(forest+time+time$^2$)</td>
<td>1.4 ± 0.6</td>
<td>1.0 ± 0.4</td>
<td>-0.6 ± 0.3</td>
<td>0.5 ± 0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ψ(canopy) p(time+time$^2$)</td>
<td>1.6 ± 0.6</td>
<td>-</td>
<td>-0.6 ± 0.3</td>
<td>0.4 ± 0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ψ(canopy) p(.)</td>
<td>1.6 ± 0.6</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 4.2 Occupancy probability of *L. catta* by percent canopy cover with upper (UCRI) and lower credible intervals (LCRI) for non-informative priors (gray lines) and informative priors (black lines).

Figure 4.3 Detection probability of *L. catta* by forest class with 95% credible intervals (CRI) for non-informative priors (a) and informative priors (b).
Figure 4.4 Detection probability of *L. catta* by time \(t^2\) with upper (UCRI) and lower credible intervals (LCRI) for non-informative priors (gray lines) and informative priors (black lines).

For *P. verreauxi*, models of best fit (DIC < 5) with the strongest covariates (95% CRI did not overlap with zero) included forest as covariate of detection probability for both modeling situations (with and without informative prior distributions) and forest as a covariate of occupancy when using informative prior distributions (Table 4.5 and 4.6). Goodness-of-fit was confirmed for each model with p-values close to 0.5 although modeling forest as a covariate of both detection and occupancy probability resulted in the lowest p-value of 0.38. Occupancy probabilities (using both informative and non-informative priors) were higher in the gallery forest with a narrow credible interval compared to a lower estimate in the dry deciduous forest with a much wider credible interval (Figure 4.5). There was no significant difference in *L. catta* occupancy probability by grazing intensity. Detection probably was higher in the dry deciduous forest with overlapping credible intervals (Figure 4.6). The use of informative priors had no affect on the relationship between forest and detection probability estimates.
Manner of detection was shown to vary by species with *L. catta* more often detected by sound (59%) and *P. verreauxi* by sight (76%). Both species were found in the canopy more frequently than on the ground (Table 4.7).

Table 4.5 Models of best fit (ΔDIC < 5) with strongest covariates (95% CRI of covariate beta distribution do not overlap with zero) of *P. verreauxi* occupancy with non-informative priors (a) and informative priors (b).ψ(.) indicates occupancy probability kept constant.

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
<th>ΔDIC</th>
<th>Bayesian p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ψ(.) p(forest)</td>
<td>302.8</td>
<td>0.0</td>
<td>0.418</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
<th>ΔDIC</th>
<th>Bayesian p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ψ(forest) p(forest)</td>
<td>301.7</td>
<td>0.0</td>
<td>0.380</td>
</tr>
<tr>
<td>ψ(.) p(forest)</td>
<td>302.8</td>
<td>1.1</td>
<td>0.347</td>
</tr>
</tbody>
</table>

Table 4.6 Beta estimates and standard deviation of covariates from best fit models of *P. verreauxi* occupancy with non-informative priors (a) and informative priors (b).

<table>
<thead>
<tr>
<th>Model</th>
<th>ψ</th>
<th>p (forest)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ψ(.) p(forest)</td>
<td>-</td>
<td>-0.6 ± 0.3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>ψ</th>
<th>p (forest)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ψ(forest) p(forest)</td>
<td>1.7 ± 0.9</td>
<td>-0.7 ± 0.3</td>
</tr>
<tr>
<td>ψ(.) p(forest)</td>
<td>-</td>
<td>-0.7 ± 0.3</td>
</tr>
</tbody>
</table>

Figure 4.5 Occupancy probability of *P. verreauxi* by forest class with 95% credible intervals (CRI) for informative priors.
Figure 4.6 Detection probability of *P. verreauxi* by forest class with 95% credible intervals (CRI) for non-informative priors (a) and informative priors (b).

Table 4.7 Manner of detection and position at time of detection frequencies for both species.

<table>
<thead>
<tr>
<th>Species</th>
<th>Manner of detection</th>
<th>Position at detection</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Audible</td>
<td>Visual</td>
</tr>
<tr>
<td><em>L. catta</em></td>
<td>0.59</td>
<td>0.41</td>
</tr>
<tr>
<td><em>P. verreauxi</em></td>
<td>0.24</td>
<td>0.76</td>
</tr>
</tbody>
</table>

Discussion

Unfortunately, it is difficult to make clear comparisons between the occupancy probability of *L. catta* and *P. verreauxi* because model-fitting resulted in the selection of models with different covariates for each species; however there are clear general trends that can be inferred from the results.

While occupancy of *L. catta* was consistently high throughout different canopy cover levels, credible error bars were noticeably narrowest at high canopy cover, or ungrazed gallery forest. Surveys occurred in the middle of the long dry season (April-October) when resource availability is at its lowest (Sauther et al. 1999) and *L. catta* relies on *Tamarindus indica* as a stable food source (Simmen et al. 2006). *Tamarindus indica* is a characteristic species of the
gallery forest (Jolly 1966, Sussman and Rakotozafy 1994) and the only species that provides food for *L. catta* year-round (Simmen et al. 2006), which could have contributed to increased *L. catta* occurrence in the gallery forest when other food was limited. *Lemur catta* has a more restricted diet consisting of two to three species for any month (Simmen et al. 2006).

Lower occupancy of *L. catta* in grazed gallery forest could have resulted from disturbance caused by herders coppicing tree to provide fodder for livestock in the long dry season. *Tamarindus indica* with obvious signs of lopping were commonly seen during surveys in the grazed gallery forest. Higher occupancy in ungrazed gallery forest corresponded to previous studies where *L. catta* was found to have higher densities in gallery forest (O’Connor 1987) and especially in undisturbed gallery forest (Axel and Maurer 2010).

*Propithecus verreauxi* occupancy was higher in gallery forest than in dry forest. However, this was true only when informative priors were used, suggesting that results were swayed, in part, by data collected in 2010. It is assumed that patterns of occupancy have remained constant since 2010, but if there have been changes in population or forest structure that have not been captured in the 2013 data collection, then these results may be misleading. Surprisingly, occupancy probability of *P. verreauxi* was not conditional on grazing presence in either forest suggesting that the species may be resistant to levels of grazing experienced at the sampling locations within this site.

One benefit of occupancy models is the additional information regarding detection probability that can be used in future studies. The higher probability of *L. catta* detection during early morning and late afternoon coincides with active periods of foraging and, in the case of the early morning, thermoregulating (Jolly 1966). *Propithecus verreauxi* have similar activity patterns (Erkert and Kappeler 2004) so it was unexpected that their detection was not dependent
on sampling time. Given that surveys were only conducted between 8:00-11:30am and 2:00-4:00pm, the lack of significance for *P. verreauxi*, and the low detection probability around 11:00am, could be exaggerated by uneven sampling throughout the day.

The varied detection probability by forest class between *L. catta* and *P. verreauxi* could be explained by differences in behavior and diet. Given 1) that *P. verreauxi* were detected by sight much more than was *L. catta* (76% and 41% respectively), and 2) *P. verreauxi* were more likely to occupy tall gallery forest (see Chapter 2), visual detection of *P. verreauxi* would be more difficult in the tall gallery forest than in the shorter, more open, canopy of dry deciduous forest. The higher frequency of sound detection for *L. catta* (59%) over *P. verreauxi* (24%) allowed for detection of *L. catta* regardless of canopy height.

Higher detection probability of *L. catta* over *P. verreauxi* may be due to the difference in group numbers in the study area. In the early 1990s, nine groups of *L. catta* were identified within Parcel 1 at Beza Mahafaly (Sussman 1991). About a decade later, a similar number were identified, although group membership had changed with some groups having dissolved or new ones formed (Gould et al. 2003). At the same time, researchers identified 54 groups of *P. verreauxi* groups within and nearby Parcel 1 (Richard et al. 2002).

A distance sampling study encountered 56 groups of *L. catta* and 102 groups of *P. verreauxi* within a much larger area (approximately 1500 ha) encompassing both parcels and the formal extension at Beza Mahafaly (Axel and Maurer 2011). Even though *L. catta* lives in groups of 6-24 individuals (Sussman 1991, Jolly et al. 2002, Gould et al. 2003) and *P. verreauxi* in smaller groups between 2-14 individuals (Richard et al. 2002), the higher number of *P. verreauxi* groups could lead to overall higher detection.
Position of *L. catta* and *P. verreauxi* at time of detection had little effect on detection probability with similarly low frequency of detection on the ground for both species (17% and 6% respectively). Despite the fact that *L. catta* is considered the most terrestrial of all lemurs, it is clear that individuals in this study preferred positions in the canopy (Goodman et al. 2006).

Given the amount of biodiversity, endemism, and endangered species found within the TDF of Madagascar, the conservation value is extremely high. Land managers need accurate occupancy data on such species of interest to make effective management decisions. Based on this study, minimally disturbed or protected areas that restrict grazing may be necessary to ensure *L. catta* conservation while unprotected areas may be useful for *P. verreauxi* conservation. Occupancy modeling was a quick and efficient tool in assessing the effects of grazing. Even with a lack of protected areas that include the tropical dry forest (Moat and Smith 2007), there is potential for these flagship species to persist in their current range with community-based conservation activities that help keep grazing intensity at moderate levels or other disturbances through occupancy modeling.
Chapter 5

Evaluating soundscape differences in a grazed tropical dry forest of Madagascar

Introduction

A soundscape consists of all acoustic energy produced from an ecosystem, including biological, anthropogenic, and geophysical sounds within a landscape (Schafer 1994, Truax 1978, Qi et al. 2008). Soundscape ecology is the study of the relationship between these acoustic sources in a system (Schafer 1994, Pijanowski 2011a, Pijanowski 2011b).

Researchers are often concerned with the unique relationship between humans and the landscape, especially the impact that humans have on landscapes. Soundscape analysis provides a novel means of assessing impacts of human disturbance on landscapes. Acoustic sound analysis has been used to characterize the biological diversity of soundscapes (Sueur et al. 2008a), visualize changes in soundscapes over time (Gage and Axel 2013), and assess the effects of human disturbances on a landscape (Joo et al. 2011).

The ability to assess ecological integrity is another valuable application of soundscape analysis (Qi et al. 2008). This measure of ecosystem biodiversity and functionality is reduced when human activities cause habitat alteration and/or fragmentation. Disturbed areas are likely to be characterized by increased anthropogenic sound and decreased biological sound activity. The biodiverse and highly endemic tropical dry forests of southern Madagascar experience widespread human disturbance in the form of livestock grazing (Sussman et al. 1994). Grazing presence in this landscape has been shown to negatively affect canopy and understory vegetation (see Chapter 2) and ring-tailed lemur (*Lemur catta*) occupancy probability (see Chapter 3). The
physical effects from grazing may also result in measurable differences in relative amounts of
anthropogenic and biological sounds.

The goal of this study was to determine if varying levels of grazing intensity resulted in
different patterns of biological sound activity in two tropical dry forest classes. It was expected
that heavily grazed areas would have less biological sound activity compared to moderately
grazed and ungrazed areas. I also expected to detect differences in sound activity by forest class
and season. While conservation efforts are generally focused on ecosystems that have limited
human-related impacts, there may be areas affected by human activities that maintain ecological
integrity suitable to sustain wildlife populations. Soundscape analysis promises to be a relatively
inexpensive means of and rapidly assessing the biological activity of landscapes.

Methods

Twelve Wildlife Acoustics Song Meter (Wildlife Acoustics, 2012) autonomous recorders
were installed at half of the twenty-four previously established sampling sites within the Beza
Mahafaly Special Reserve (see Chapter 1). The twelve recorder locations were chosen during
installation in January 2013 followed by twelve additional sites for vegetation and wildlife
sampling in June 2013. Recorders were installed in two forest classes (gallery and dry
deciduous) and three levels of grazing intensity (ungrazed, moderately grazed, and heavily
grazed) resulting in two recorders assigned to each combination of forest and grazing category.
Each sensor was installed in a tree roughly two to three meters above ground. Recorders were
programmed to record a one minute acoustic sample every fifteen minutes for twelve months,
beginning in early January 2013 and recording through the end of December 2013. Acoustic
samples were recorded in the Waveform Audio File Format (WAV) at a frequency of 24,000 Hz
with a recorded frequency range up to 11 kHz. After collecting the recorded files and accounting for days without sampling data due to battery failure, a total of 286,485 recordings were collected. All recordings were resampled to 22,050 Hz to conform to parameters of code obtained through the R Project using the seewave (Sueur et al. 2008b), tuneR (Ligges et al 2013), and soundecology (Villanueva-Rivera Pijanowski 2014) packages.

Resulting sound files were analyzed using the normalized difference soundscape index (NDSI), a ratio of biological sounds to sounds associated with anthropogenic activities (Joo 2008, Qi et al. 2008, Kasten et al. 2012) that serves as an indicator of biological activity:

\[
\text{NDSI} = \frac{\beta - \alpha}{\beta + \alpha}
\]

where \(\alpha\) is the anthrophony, or the amount of acoustic energy from human-generated sound, and \(\beta\) is the biophony, or acoustic energy from biological sounds. Anthrophony is categorized as all sound energy detected between 1 and 2 kHz and biophony as all sound energy detected between 2 and 11 kHz. All sound energy below 1kHz is considered noise and not included in the index. In more urban locations, examples of sources of anthrophony include traffic, industrial noise, and sirens. In this site, examples of anthrophony sources include livestock, motor bikes, and ox carts. NDSI values range from -1 to 1, with -1 indicating a soundscape comprise of primarily human related sounds and +1 indicating a completely biological soundscape.

Data were summarized, and then tests for significant difference were made using either an ANOVA or a non-parametric Kruskal-Wallis test. A daily average NDSI was calculated for each day at each sensor, and then data were tested for spatial autocorrelation using a Mantel test. A one way ANOVA or Kruskal-Wallis test was used to test for differences in mean daily NDSI values 1) between forest classes (gallery and dry deciduous) and 2) between seasons (wet and dry). A two-way ANOVA was used to test for differences in mean daily NDSI by both forest
class and season. Finally, a six-way pairwise comparison of means (Tukey’s HSD) was used to identify significant differences in mean daily NDSI values between all forest and grazing categories. In addition, time series plots of mean daily NDSI and mean daily NDSI variance were created to visually interpret patterns by season, forest class, and grazing intensity. All statistical analyses were conducted using the software program R (R Core Team 2013) and time series were constructed using the zoo package (Zeileis, A. and Grothendieck, Gabor. 2005).

Results

A mantel test for spatial autocorrelation failed to reject the null hypothesis that sites were spatial independent of one another (p-value=0.50, α=0.05), allowing us to treat sites as independent samples for analysis. In a test of homogeneity of variances, the F-test revealed that variances were unequal when comparing NDSI by forest class, so a Kruskal-Wallis test was conducted. There was no significant difference in mean daily NDSI by forest type across the entire 2013 sampling period (Table 5.1, Figure 5.1). In a one-way ANOVA, significantly lower NDSI values were detected during the dry season (Table 5.2, Figures 5.2 and 5.3).

Table 5.1 Kruskal-Wallis results for mean daily NDSI values forest class.

<table>
<thead>
<tr>
<th>Degrees of freedom</th>
<th>$\chi^2$</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest class</td>
<td>1</td>
<td>1.6939</td>
</tr>
</tbody>
</table>

Table 5.2 One way ANOVA of mean daily NDSI values by season.

<table>
<thead>
<tr>
<th>Degrees of freedom</th>
<th>Sum of squares</th>
<th>Mean square</th>
<th>F value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Season</td>
<td>1</td>
<td>3.52</td>
<td>3.516</td>
<td>343.9</td>
</tr>
<tr>
<td>Residuals</td>
<td>3234</td>
<td>33.06</td>
<td>0.010</td>
<td></td>
</tr>
</tbody>
</table>
Figure 5.1 Time series plot of mean daily NDSI values for gallery and dry deciduous sites (n=12 recorders, averaged by forest class). Area shaded in grey indicates rainy season and white indicates dry season.
Figure 5.2 Time series plot of mean daily NDSI values from ungrazed, moderately grazed, and heavily grazed gallery sites. (n=6 recorders, averaged by grazing intensity). Area shaded in grey indicates rainy season and white indicates dry season.
Figure 5.3 Time series plot of mean daily NDSI values from ungrazed, moderately grazed, and heavily grazed dry deciduous sites. (n=6 recorders, averaged by grazing category). Area shaded in grey indicates rainy season and white indicates dry season.
A general trend was observed in mean daily NDSI values for forest class by season; higher mean daily NDSI values were observed in rainy season than in the dry, however, mean daily NDSI values for combined forest class plus grazing intensity did not vary significantly across the entire sampling period (Table 5.3, Figure 5.4). However, NDSI in moderately grazed gallery forest was significantly lower than ungrazed gallery forest. But NDSI in the heavily grazed gallery forest was not significantly different from NDSI in the ungrazed gallery (Figure 5.2). The pattern in the dry deciduous forest is a little different. Again, mean daily NDSI in the moderately grazed dry deciduous forest is significantly lower than in the ungrazed dry deciduous forest, but in this forest class, the NDSI in heavily grazed forest is also lower than in ungrazed. (Figure 5.3). There was frequent overlapping of mean daily NDSI values observed for all forest and grazing categories without one individual category displaying a significant difference from all others but the pairwise comparisons are meaningful.

Time series plots of mean NDSI and variance for each site indicate seasonal difference in variance across different grazing intensities. Ungrazed forests display consistently lower variance than in both grazed categories in both forests (Figure 5.5). Higher variance is also evident during the rainy season in the gallery (Figure 5.6) and dry deciduous forest (Figure 5.7).
Table 5.3 Mean and standard error of mean daily NDSI values by forest class and grazing intensity for the entire sampling year. Means with the same letters are not significantly different (ANOVA, Tukey’s HSD, $\alpha=0.05$, df=3230, F value=17.41).

<table>
<thead>
<tr>
<th></th>
<th>Gallery</th>
<th>Dry deciduous</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ungrazed</td>
<td>Mod.</td>
</tr>
<tr>
<td>Entire year</td>
<td>0.80±0.11 $^a$ $^b$</td>
<td>0.76±0.11 $^d$</td>
</tr>
</tbody>
</table>

Figure 5.4 Boxplot of mean daily NDSI values by forest and grazing intensity for entire sampling season.
a. Ungrazed

b. Moderately grazed

c. Heavily grazed

Figure 5.6 Time series plot of mean daily NDSI values averaged by forest class for ungrazed (a), moderately grazed (b), and heavily grazed sites (c). Area shaded in grey indicates rainy season and white indicates dry season.
a. Ungrazed

b. Moderately grazed

c. Heavily grazed

Figure 5.7 Time series plot of mean daily NDSI values and variance for each recorder in the gallery forest by grazing intensity: ungrazed (a), moderately grazed (b), and heavily grazed sites (c). Area shaded in grey indicates rainy season and white indicates dry season.
a. Ungrazed

b. Moderately grazed

c. Heavily grazed

Figure 5.8 Time series plot of mean daily NDSI values and variance for each recorder in the dry deciduous forest by grazing intensity: ungrazed (a), moderately grazed (b), and heavily grazed sites (c). Area shaded in grey indicates rainy season and white indicates dry season.
Discussion

The observed differences in biological sound activity between the rainy and dry seasons were expected given the extreme seasonality of this tropical dry forest system. During the rainy season months, between November and March, the forest produces markedly higher amounts of young leaves, flowers and fruits (Hladik et al. 1980, Sauther 1998) providing food for multiple taxa. This would cause an increase in foraging and other social behavior resulting in more acoustic activity detected by the sensors, as acoustic signals are common in communication during mating times, territory defense, and predation (Bradbury and Vehrencamp 2011). The days are longer during these rainy months, increasing the amount of sound activity from diurnal species during the longer daylight hours. The rainy season also corresponds with the highest annual temperatures, allowing for increased activity in the mornings and late afternoons when animals do not need to allocate time and energy to conserving heat.

The dry season, between April and October, is when the deciduous vegetation lose leaves, flowers, and fruits, decreasing the food supply for many species. This season is also marked by shorter and cooler days. When temperatures are cool, many wildlife species allocate large periods of time to thermoregulating in the morning. The two diurnal lemur species found within the study site (Lemur catta and Propithecus verreauxi) have each been known to spend long periods of time basking in the sun to increase body temperature during the mornings of colder days (Kelley 2013, Richard 1974). Decreased activity from inactive thermoregulating combined with shorter days could certainly contribute to the markedly lower biological sound activity recorded during the dry season.

I would have expected a high amount of biological sound activity in the gallery forest from wildlife feeding on T. indica in the gallery forest during the dry season. Given that this is
not the case, there may be evidence for more equal resource utilization between forest classes during the dry season than previously expected. As seen in chapter 2, the plant species composition is significantly different between gallery and dry deciduous sites, providing a wider range of resources. The close proximity of forest classes allows wildlife to travel between both distinct habitats, utilizing as many resources as possible.

The generally lower biological sound activity detected in the grazed forests indicates less biological activity in grazed forests that may be due to grazing impacts on forest vegetation. Increased grazing pressure resulted in more compact soils, lower leaf litter thickness, and decreased seedling number, cover, and richness (see Chapter 2). These impacts on the habitat could decrease plant availability to wildlife, resulting in less biological sound detected. The lack of grazing pressure in ungrazed forest could have increased wildlife activity due to better quality or more abundant plant resources, implying more suitable habitat for wildlife. This is further supported by the higher occupancy probability of *L. catta* in ungrazed forests (see Chapter 4).

The overall lower variance in ungrazed forest implies a more stable soundscape composition. These forests may suffer from fewer extremes in the soundscape likely due to a more or less unchanging forest structure. Grazed forests may experience much higher variation in biological sound due to erratic nature of disturbance events such as livestock grazing. The overall higher variance detected during the rainy season could result from habitat and wildlife responses to inconsistent weather patterns. The rainfall patterns in Madagascar are highly variable (Dewar and Wallis 1999), with amount of rainfall fluctuating within and between multiple years. There was a significant rain event around mid February and there was a corresponding dip in variance even in the ungrazed forest during that time.
Soundscape analysis is a promising new method for fast and efficient measurement of biological activity that could be easily implemented in monitoring schemes of sound activity in human-impacted habitats worldwide.
References


Environmental Systems Research Incorporated. ArcMap 10.0.


May 1, 2013

Lyndsay L. Rankin
941 12th Ave, Apt 1
Huntington, WV 25701

Dear Ms. Rankin:

This letter is in response to the submitted thesis abstract titled “Assessment of Ecological Integrity of Grazed Tropical Dry Forests in Madagascar.” After assessing the abstract it has been deemed not to be human subject research and therefore exempt from oversight of the Marshall University Institutional Review Board (IRB). The Code of Federal Regulations (45CFR46) has set forth the criteria utilized in making this determination. Since the information in this study does not involve human subjects as defined in the above referenced instruction it is not considered human subject research. If there are any changes to the abstract you provided then you would need to resubmit that information to the Office of Research Integrity for review and a determination.

I appreciate your willingness to submit the abstract for determination. Please feel free to contact the Office of Research Integrity if you have any questions regarding future protocols that may require IRB review.

Sincerely,

Bruce F. Day, ThD, CIP
Director
Office of Research Integrity