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Modeling the potential distribution of endangered, endemic Hibiscus brackenridgei on Oahu to assess the impacts of climate change and prioritize conservation efforts

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A thesis submitted in partial satisfaction

of the requirements for the degree Master of Arts

in Geography

by

Corey Marie Rovzar

2012

ABSTRACT OF THE THESIS

Modeling the potential distribution of endangered, endemic *Hibiscus brackenridgei* on Oahu to assess the impacts of climate change and prioritize conservation

by

Corey Marie Rovzar

Master of Arts in Geography

University of California, Los Angeles, 2012

Professor Thomas W. Gillespie, Chair

In the Hawaiian dry forest, 45% of all tropical dry forest trees and shrubs are on the federal threatened and endangered species list. Research is needed to focus on understanding the current range of these endangered species, the factors that affect their current and future distributions, and ultimately, possible areas for the most successful restoration to be undertaken. This research uses species distribution modeling to predict the potential range of *Hibiscus brackenridgei*, the state flower of Hawaii and a federally endangered species found on Oahu. We used presence data and the modeling algorithm Maxent to model the current potential distribution of *H. brackenridgei*, identify climate and environmental variables that influence the species' distribution, and model the species' predicted future distribution based on a range of projected climate change scenarios. Statistical analysis suggests that the Maxent models accurately predict

the species' distribution, and therefore, may be useful for conservation management. Comparing the current model with the future models of changes for 2060-2089, changes in the potential niche of *H. brackenridgei* only range from -4% to 14%. This suggests that the predicted changes in climate, under both low (B2a) and high (A2a) global emissions scenarios, may not significantly impact the future distribution of *H. brackenridgei* on Oahu. We identified a total of 115 km^2 of very highly ($\geq$0.70) and highly ($\geq$ 0.50) suitable habitat which represents potential areas where restoration projects could be implemented. This research suggests that threats like habitat loss, fire, invasive species, and grazing may be more important than climate for the future conservation of Hawaiian dry forest species.

The thesis of Corey Marie Rovzar is approved.

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INTRODUCTION

Tropical dry forests in Hawaii are among the most endangered forest types in the world with 45% of endemic trees and shrubs on the federal threatened and endangered species list (Pau et al. 2009). While Hawaiian dry forest ecosystems previously contained high species richness and endemism compared with other habitats in Hawaii (Rock 1913), over 90% of the dry forest area has now been destroyed resulting in widespread species loss (Bruegmann 1996; Cabin et al. 2000; Sakai et al. 2002). However, despite their conservation importance, there is little information on the current distribution of Hawaiian dry forest species or information on potential sites for endangered species restoration (Pau et al. 2009).

Hibiscus brackenridgei, the state flower of Hawaii, is a federally endangered species found in the Hawaiian dry forest (Wagner et al. 1990). The species is native to lowland dry/mesic forests and shrublands and occurs on slopes, cliffs, and arid ledges between elevations of 24-490 meters (Mansker 2002). On Oahu, the species is scattered throughout the Wai'anae Mountains from Puu Pane to Kealia-Kawaihapai and the Dillingham Military Reservation (U.S. Fish and Wildlife 1999; Oahu Army Natural Resources Program 2010). According to the US Fish and Wildlife Service, only five populations are known to remain on Oahu (Mansker 2002; Oahu Army Natural Resources Program 2010). Primary threats to the species include grazing by feral ungulates, invasive plants, fire, and land degradation (Cabin et al. 2000). There has been minimal research regarding the plant's life history especially regarding pollination, biology, longevity, environmental requirements, and limiting conditions (Mansker 2002). Furthermore, it is unclear how climate change will impact the species range.

Species distribution modeling is one method for evaluating the potential niche of a species and has been increasingly used to address problems across a variety of fields including biogeography, ecology, conservation biology, and climate change science (Guisan & Thuiller 2005; Gillespie et al. 2008; Franklin 2009; Richardson & Whittaker 2010; Feeley & Silman 2011). Species distribution models relate a species' geographic/spatial distribution to environmental predictor variables, such as climate, and can be used to map both current and future species' distributions (Graham et al. 2004; Guisan & Thuiller 2005).

Species distribution model algorithms require occurrence information of the target species in one of two forms: presence/absence data (typically from field surveys) or presence only data which can be from field surveys and/or museum or voucher specimens. By evaluating this data, a probability of species occurrence can be modeled for areas with an absence of location data (Zaniewski et al. 2002). Analyzing the current extent of a species range and generating a predictive model for its distribution allows for a better understanding of its current endangerment and offers insight into areas which may be most suitable for regenerating populations. Species distribution modeling has been shown to be a powerful tool in improving research in conservation and restoration (Araújo & Williams 2000; Elith et al. 2006) and is especially useful in tropical regions with deficient geographic locality data resulting from small sample sizes or imprecise locations of specimens (Graham et al. 2004). Evaluating factors which influence the distribution of endangered populations enables conservation programs to improve their overall success (Corsi et al. 1999).

Previous findings suggest that geographic distribution is a principle factor for evaluating patterns of endangerment for individual species on the Hawaiian Islands (Sakai et al. 2002). Although there has been ongoing restoration of endangered dry forest tree species in Hawaii, none have used species distribution modeling to evaluate potential restoration sites.

This research had three primary objectives. First, we modeled the potential distribution of *H. brackenridgei* on Oahu under current conditions and identify the climate and environmental variables with the greatest effect on its distribution. Second, we model future (2060-2089) distributions of *H. brackenridgei* under two climate model scenarios to assess the threat of climate change on the species. Third, we identified priority areas for conservation based upon current and future predictions of habitat suitability.

METHODS

Study Site

This research was undertaken on the island of Oahu, Hawaii, which is approximately 3.7 million years old and covers an area of 1,546 km^2 (Fig. 1; Fleischer et al. 1998). Its two major mountain ranges, the Wai'anae's in the west and Ko'olau's in the east, are extinct shield volcanoes that roughly parallel each other. Oahu's dominant climatic variation is rainfall, with the rainy season between November and March and the dry season from April to October. Native tropical dry forests, scrublands, and grasslands historically occur in the low elevations and rainshadow sides of Oahu.

Data Collection

This research considered 49 geographic point locations for *H. brackenridgei*, the only known living occurrences on Oahu (Fig. 2; Oahu Army Natural Resources Program 2010). Only presence data were evaluated for this study. Although 49 geographic point locations were considered, some of them fell within the same grid cell (1 km^2). As a result, Maxent only included 16 occurrences in the model while the other presence data were considered to be duplicates.

Environmental Variables

We downloaded climate data from WorldClim version 1.4 (Hijmans et al. 2005). These include

19 bioclimatic variables at a 1 km (30 arc second) pixel resolution which are derived from monthly temperature and rainfall estimates, and represent biologically meaningful variables for characterizing species distributions. We used elevation data from NASA's Shuttle Radar Topography Mission (SRTM) to calculate slope and aspect using ArcGIS 10 (ESRI, Redlands, CA, USA). Additionally, we included soil order (9 categories) and great group (31 categories) in our model and converted the shapefiles from vector to raster format (Hawaii Statewide GIS Program 2011). Land use data developed from Landsat ETM satellite imagery taken in 2000 was also included in our model (National Oceanic and Atmospheric Administration Coastal Services Center 2012). Before adding soil order, great group, and land use to our model, we resampled each variable at a 30 arc second resolution.

Lastly, we downloaded projected future climate variables for 2060-2089 from the International Center for Tropical Agriculture (CIAT) which contains empirically downscaled climate change data (Ramirez & Jarvis 2008). The CIAT initially downloaded this data from the IPCC data portal and then reformatted each climate variable from the WorldClim database with a spline interpolation algorithm. This research utilized an ensemble of Global Circulation Models (GCMs) in order to provide a robust estimate of temperature and precipitation changes. Ensemble averages have been found to better represent observed climate patterns compared with individual models by filtering out individual model biases (Cubasch et al. 2001; Giorgi & Mearns 2002; Randall et al. 2007; Beaumont et al. 2008). We created the GCM ensemble by averaging climate projections from CSIRO-MK2, HCCPR HADCM3, NIES99, and CCCMA-GCM2. We used two Special Report on Emissions Scenarios (SRES) to model potentially different outcomes of climate change as they relate to greenhouse gas emissions. The first, A2a, is a scenario that assumes high global energy requirements and therefore, higher greenhouse gas emissions. In contrast, the B2a scenario assumes lower energy requirements and thus, lower emissions. Both scenarios involve higher regional, versus global, economic growth (Nakicenovic 2000). These scenarios were chosen because they represent widely used end-members from a range of potential future emissions levels (Beaumont & Hughes 2002; Thuiller et al. 2005; Araújo et al. 2006; Svenning & Skov 2006; Tuck et al. 2006; Beaumont et al. 2008).

Despite the widespread use of statistical downscaling methods to infer climate change impacts, it is important to acknowledge the shortcomings of this approach (Wiens & Bachelet 2010). Statistical downscaling assumes that large-scale atmospheric processes as well as regional forcing influence regional climate (Tabor & Williams 2010). Additionally, statistical downscaling assumes stability between climate relationships at different scales and compounds uncertainty of the coarser GCMs due to the interpolation or extrapolation of patterns to finer resolutions (Gonzalez et al. 2010; Wiens & Bachelet 2010). However, because GCM outputs are biologically coarse, statistical downscaling is a viable solution for appropriately scaling species distribution models to a level relevant for conservation planning (Seo et al. 2009). Furthermore, statistically downscaled climate data with grid sizes of 1 km^2 are globally available and are at a sufficient resolution for identifying suitable areas for restoration.

Modeling Algorithm

We used the modeling algorithm Maxent to model the distribution of *H. brackenridgei*. Maxent is a machine-learning program that applies maximum-entropy techniques to predict the probability of species occurrence based on species locality data and environmental limitations (Phillips et al. 2006). Compared with other modeling methods, Maxent performs best with both spatially biased data and limited presence data (Elith et al. 2006; Pearson et al. 2007; Loiselle et al. 2008; Riordan & Rundel 2009; Costa et al. 2010). Additionally, Maxent measures the contribution of each environmental variable to the predicted species distribution which allows for an understanding of variable importance (Ortega-Huerta & Peterson 2008; Kumar & Stohlgren 2009). Accurate absence data often does not exist or is difficult to obtain, resulting in the need to rely on presence-only records (Graham et al. 2004; Elith & Leathwick 2007; Riordan & Rundel 2009). Maxent only requires presence data and can be utilized across a range of sample sizes (Phillips et al. 2006). Despite a lack of absence data, previous research suggests that presence-only data is effective for species distribution modeling (Elith et al. 2006). For this study, we used Maxent version 3.3.3a to generate species distribution models (Philips et al. 2006). We added the 19 bioclimatic variables, slope, aspect, land use, soil, and the species' geographic point locations into Maxent and used default parameters to produce a model of the probability of *H. brackenridgei* occurrence on Oahu based on these environmental variables. After generating the model, we performed principal component analysis (PCA) on the 19 bioclimatic variables using a correlation matrix to reduce dimensionality and correlations and re-ran the model using the appropriate variables.

Next, we projected the model under both the A2a and B2a scenarios to generate two future habitat suitability maps for comparison with the contemporary model. To assess the significance of any changes, we conducted paired t-tests between the current and future model probabilities.

Restoration Application

In order to provide insights for conservation, we created a habitat suitability index which assigns a categorical value for a range of probabilities. Areas with a probability of occurrence ≥ 0.70 correspond with very high suitability. Similarly, areas between 0.50 - 0.70 probability correspond with high suitability, 0.30 - 0.50 with medium suitability, 0.10 - 0.30 with low suitability, and 0.00 - 0.10 with not suitable. To evaluate the practical usefulness of the predicted climate change impacts on the potential distribution of *H. brackenridgei*, we generated a robust model considering both current and future a2a climate changes. Areas classified by habitat suitability under current conditions only changed categories if the future changes in probability were significant enough to either downgrade or elevate the suitability status of the area. For example, very highly suitable areas have probabilities between 0.70-1.00. If a very highly suitable area with a probability of 0.70 under current conditions decreased by 0.10 in the future, then the area became highly suitable (0.50 - 0.70) under the robust model. Similarly, an area could experience a significant increase in probability and therefore, elevate in habitat suitability status. This approach considers the overall magnitude of change and enables potential changes in climate to be evaluated conservatively. We then overlayed our model onto landownership, Oahu reserve, and currently managed *H. brackenridgei* site shapefiles to evaluate the effectiveness of current management in protecting suitable habitat for *H. brackenridgei* (Hawaii Statewide GIS Program 2011; Oahu Army Natural Resources Program 2010). Furthermore, we

Lastly, to visualize restoration areas, we created GIS pixel boundary layers in Keyhole Markup Language (KML) format for the very high, high, and medium habitat suitability categories and overlaid them on satellite imagery using Google Earth (http://earth.google.com; Fig. 3). This allowed for a high resolution analysis of areas which may be suitable for restoration based on present and future distribution models.

Model Validation

Validating a species distribution model is essential if it is to be used for conservation purposes (Elith et al. 2011). To measure the predictive success of a model, available data will often times be divided into training and test groups. However, this method is inappropriate for this study owing to small sample size (Pearson et al. 2007). Instead, we conducted 10 bootstrap iterations to evaluate the performance of the model in predicting the species' potential distribution. Bootstrapping involves sampling the data-set randomly with replacement and analyzing the mean and range from the bootstrap samples to validate the model (Pearson et al. 2007). This study considers both threshold-dependent and threshold-independent metrics for model validation. Omission rate is a threshold-dependent metric which represents the fraction of test localities located outside the predicted area. For presence-only data, maintaining a low omission rate is essential for generating informative predictions of a species' potential distribution (Riordan & Rundel 2009). Because *H. brackenridgei* is immobile and unlikely to be present in unsuitable areas, there was high confidence that the presence data are correct. As a result, omission generated by any presence record was attributed to model error. We selected a minimum training presence threshold which identifies pixels at least as suitable as the species' recorded localities and allows for determining the minimum predicted area possible (Pearson et al. 2007). In addition, we evaluated the Area under the Receiver Operating Curve (AUC) which is a threshold-independent metric. With presence-only data, the AUC curve represents the probability that a presence location is ranked higher than a background locality chosen randomly (Phillips et al. 2006; Phillips & Dudik 2008). The AUC value ranges between 0 and 1.0 with a random prediction of 0.5 (Riordan & Rundel 2009). Models generating AUC values greater than 0.75 are considered potentially useful for predicting a species' distribution (Elith et al. 2011). A one-tailed Wilcoxon rank sum test was used to evaluate if the model AUC was higher than the 0.5 AUC score of the random prediction.

RESULTS

Model Predictions

Demonstrated by the AUC score (0.95), the model was successful in reliably predicting the distribution of *H. brackenridgei* on Oahu. Compared to the random prediction (0.5), the AUC score was highly statistically significant (AUC=0.95, $p < 0.001$, one-tailed Wilcoxon rank sum test of AUC, stdev= 0.027). This suggests that the model is potentially useful for predicting the distribution of *H. brackenridgei* and that the climate and topographic variables have a discernible effect on the species' regional distribution. In addition, the ROC omission rate at a minimum training presence was zero, suggesting that no test localities fell outside of the predicted suitable areas. This is attributed to the assumption that the presence data were accurate due to the immobility of the species and high confidence that the species would not be found in unsuitable habitat. The current and future species distribution models display the highest probability of occurrence in north-western Oahu along the outer ridges of the Waianae mountain range (Fig. 3, 4, 5).

Variable Contribution

PCA analysis of the 19 bioclimatic variables reduced the dimensionality of our data set to precipitation of the driest month, mean diurnal temperature range, slope, and aspect. Together, these variables were associated with 32.7%, 29.3%, 27.5%, and 10.5%, respectively, of the variability in contemporary *H. brackenridgei* distribution. Variables highly correlated with mean diurnal temperature range include isothermality, annual temperature range, and temperature seasonality. Thus, mean diurnal temperature range represents overall temperature variability. Variables highly correlated with precipitation of the driest month include precipitation of the driest quarter, precipitation seasonality, and precipitation of the warmest quarter. We interpreted these correlations as representing summer precipitation. We ran our models using mean diurnal temperature range and precipitation of the driest month because they produced the best AUC scores compared with their correlated variables. We excluded the other bioclimatic variables, soil, and landuse because they contributed < 1% to the models.

Impact of Climate Change

The A2a change detection shows a maximum decrease of 4% and a maximum increase of 14% change in suitability while the B2a change detection suggests a maximum decrease of 3% and a maximum increase of 13%. Although the changes are statistically significant ($p < .001$), ultimately they are not practically useful for conservation management. The robust model shows that only two areas predicted very highly suitable in the current model experienced significant change which downgraded them to highly suitable (Fig 6.). Similarly, only one area predicted highly suitable under current conditions downgraded to medium suitability. This suggests that although climate variables are important for the distribution of *H. brackenridgei*, climate change, at least for the time period and emissions scenarios studied here, may not significantly affect the species' range.

Visualizing Restoration

Comparing areas predicted highly and very highly suitable with land variables relevant to conservation shows that the model may benefit conservation management efforts for *H. brackenridgei* (Table 1). Considering all highly and very highly suitable areas, 49% falls within public land while 26% is private land. Furthermore, only 24% of these areas is found within current protected and managed areas for *H. brackenridgei*. The land use for these areas is dominated by scrub/shrub (80%), followed by evergreen forest (8.7%), grassland (7.8%), cultivated land (1.7%), developed (0.9%), and bare land (0.9%). Thus, the highly and very highly suitable areas may be practical sites for restoration due to the high percentage of favorable land cover.

DISCUSSION

This research shows that it is possible to model the potential distribution of species with low numbers of occurrences over small areas. Most Pacific islands are geographically isolated and small, resulting in high numbers of endangered species and high extinction rates (Gillespie et al. 2008). As a result, conservation on these islands is a priority, and new methods are needed to improve its efficiency. While previous studies identify both climate change and land use change as primary threats to reserve effectiveness (Araújo et al. 2004; Thomas et al. 2004; Whittaker et al. 2005; Rodgriguez et al. 2007), our findings suggest only modest impacts of climate change by the late 21st century. Our study supports the growing notion that species distribution modeling is a cost-effective tool which allows for the analysis of the potential impacts climate change may have on a species range as well as the ability of the current reserve to protect future suitable habitat (Rodríguez et al. 2007). This research provides a framework for modeling climate change impacts on the distribution of endangered species on small, remote Pacific islands. Evaluating changes in species range which may result from climate change allows for reserves to make changes necessary to ultimately protect endangered species from extinction.

Currently protected and managed areas for *H. brackenridgei* account for only 24% of combined highly and very highly suitable habitat. Thus, current management may not provide adequate protection for habitat most suitable for the species both in the present and future. Our model suggests that restoration of *H. brackenridgei* should be prioritized in the north-western Waianae mountains of Oahu in order to allow for the most efficient and successful conservation of the species. This area contains little development and is dominated by scrub, evergreen forests, and grasslands, and thus, suitable for restoration. Furthermore, a number of protected areas occur in this region including Kaena Park, the Honouliuli Forest Reserve and the Makua

Military Reserve, which will help protect the restored populations from anthropogenic disturbance. Although restoration within designated conservation sites would provide protection for the planted individuals, it is important to consider other suitable sites due to the carrying capacity within each reserve.

In order to use species distribution models to inform conservation, it is beneficial to have a visualization tool which facilitates interaction between scientists and project managers. Google Earth is a free visualization tool which not only facilitates data analysis and communication of results, but also enables scientists to engage their target audience (Guralnick et al. 2007). For endangered species distribution modeling, Google Earth bridges the gap between researchers and project managers by improving communication. Through collaboration, scientists may provide valuable information regarding potential restoration sites while project managers contribute their insights for the best conservation methods. Ultimately, Google Earth is a transformative tool which will facilitate the application of species distribution models in conservation management plans. For restoration of *H. brackenridgei,* Google Earth allows for a greater understanding of the underlying vegetation and topography and their suitability for the species (Fig. 7).

Our research suggests that climate change may not significantly impact the range of *H. brackenridgei.* As a result, other factors may pose a greater threat to the conservation of the species, such as fire and competition with invasive species. For example, in 2007, the Waialua fire caused much of the Wai'anae mountain habitat to burn, resulting in the destruction of mature plants while increasing the number of seedlings and immature plants. After the fire, non-native grasses dominated the habitat and outcompeted *H. brackenridgei* seedlings resulting in difficulties for the endangered population's regeneration (Oahu Army Natural Resources Program 2010). Furthermore, invasive grasses threaten dry forest species by hindering their germination, establishment, and growth, as well as increasing the frequency and intensity of fires (Hughes et al. 1991; D'Antonio & Vitousek 1992; Cabin et al. 2002). More frequent and intense fires results in a positive feedback loop in which woody vegetation further declines causing fire-adapted grasses to expand which perpetuates fire events (D'Antonio & Vitousek 1992; Cabin et al. 2002). Climate change may indirectly impact the distribution of *H. brackenridgei* by favoring the expansion of invasive grasses. However, more research is needed to understand how each invasive species in the Hawaiian dry forest will respond to future climate change. Understanding of the overall impact of different threats on the species will allow for selection of restoration sites that will provide the species with the greatest chance of survival. Because of the difficulty in accessing the individuals in unmanaged regions of the Waianae Mountains, we suggest that restoration be prioritized in these already managed areas predicted to be highly or very highly suitable.

The high probability of species occurrence in the northwest region of Oahu is most likely due to the combination of mean diurnal temperature range, precipitation of the driest month, slope, and aspect. Mean diurnal temperature range (calculated by subtracting the mean of the monthly minimum temperature from the mean of the monthly maximum) provides insight into temperature variation. For most regions in the world, the diurnal temperature range has decreased resulting from an increase in minimum temperature relative to maximum temperature (Karl et al. 1993; Mitchell et al. 1995; Wu, Q. 2010). For this model, areas with a higher probability of occurrence correlated with larger mean diurnal temperature ranges. This suggests that increasing minimum temperatures will restrict the range of *H. brackenridgei* while areas that maintain a greater difference between the maximum and minimum monthly temperatures will be most suitable for the species. Another variable driving the modeled distribution is precipitation of the driest month. This variable represents the dry season which distinguishes dry from wet tropical forests and drives species richness within the dry forest (Pau et al. 2012). The livelihood of *H. brackenridgei* depends upon the persistence of a dry season which significantly impacts the species' distribution. Lastly, *H. brackenridgei* populations tend to grow best on steep slopes, and are therefore, more likely to be found along the ridges of mountain ranges. However, while these variables may be important drivers for the distribution of *H. brackenridgei,* our research suggests that future changes in these climate variables not be great enough to severely impact the species range.

Although the model provides insights for the restoration of *H. brackenridgei*, it should not be used as an absolute identification of the species' range. Because the distribution values are estimated from climate and environmental variables, many other factors, such as dispersal and competition, are not considered, which will ultimately affect the distribution of the species (Pearson & Dawson 2003). While a higher resolution analysis would reduce the number of suitable areas and thus, provide greater specificity, the coarse resolution provides valuable information regarding current management for *H.brackenridgei*. Additionally, the presence data used may be biased by collecting site accessibility within a habitat as well as the tendency for collection to occur in clusters (Kadmon et al. 2004; Moerman & Estabrook 2006; Schulman et al. 2007; Loiselle et al. 2008; Feely & Silman 2011). Many of the locality points occur in the northwest corner which may introduce locational bias. The overall effect of limited presence data is the tendency for species distribution models to underestimate species' ranges and therefore, overestimate habitat loss and risk of extinction (Feely & Silman 2011). It is also important to recognize the limitations of the modeling program. It has been argued that to increase the accuracy of Maxent there must be improved regularization and greater applications of the model to evaluate its success (Ortega-Huerta & Peterson 2008).

Future work would benefit greatly from increased field survey. Random or systematic sampling in the field would minimize locational bias and improve the accuracy of the model (Feely & Silman 2011). Another way to improve the accuracy of the model is to include more variables, especially remotely sensed metrics of leaf area index (LAI) and canopy moisture and structure, which have been found to complement climatic variables resulting in better distribution models (Saatchi et al. 2008). Modeling the distribution of the species at a higher resolution may allow for a greater understanding of the impacts of climate change within micro-climates. However, to study climate change impacts concomitant improvements in the spatial resolution of climate models would also be required. Lastly, modeling the impact of threats other than climate change on the distribution of *H. brackenridgei* can provide further insight for management decisions.

CONCLUSION

Our results suggest that although climate variables are important drivers, climate change may not pose a significant threat to the distribution of *H. brackenridgei* on Oahu. As a result, it is important for research to evaluate other factors which may pose a greater threat to the species. Furthermore, comparing areas predicted to be very highly (≥ 0.70) or highly (≥ 0.50) suitable with information regarding the current protection of the species suggests that there is room for improvement regarding management of *H. brackenridgei* on Oahu. This research provides a template for modeling other endangered dry forest species on Oahu. Comparing predicted distributions of individual species and evaluating overlapping ranges would allow for an understanding of the threat of climate change as well as identification of potential restoration sites for dry forest communities. Furthermore, this research suggests that threats such as habitat loss, grazing, fire, and invasive species may have a greater impact than climate change on the future preservation of dry forest species on Oahu. Beyond Oahu, endangered dry forest species should be modeled for all the Hawaiian Islands in order to devise a management strategy for conservation of the Hawaiian dry forest ecosystem.

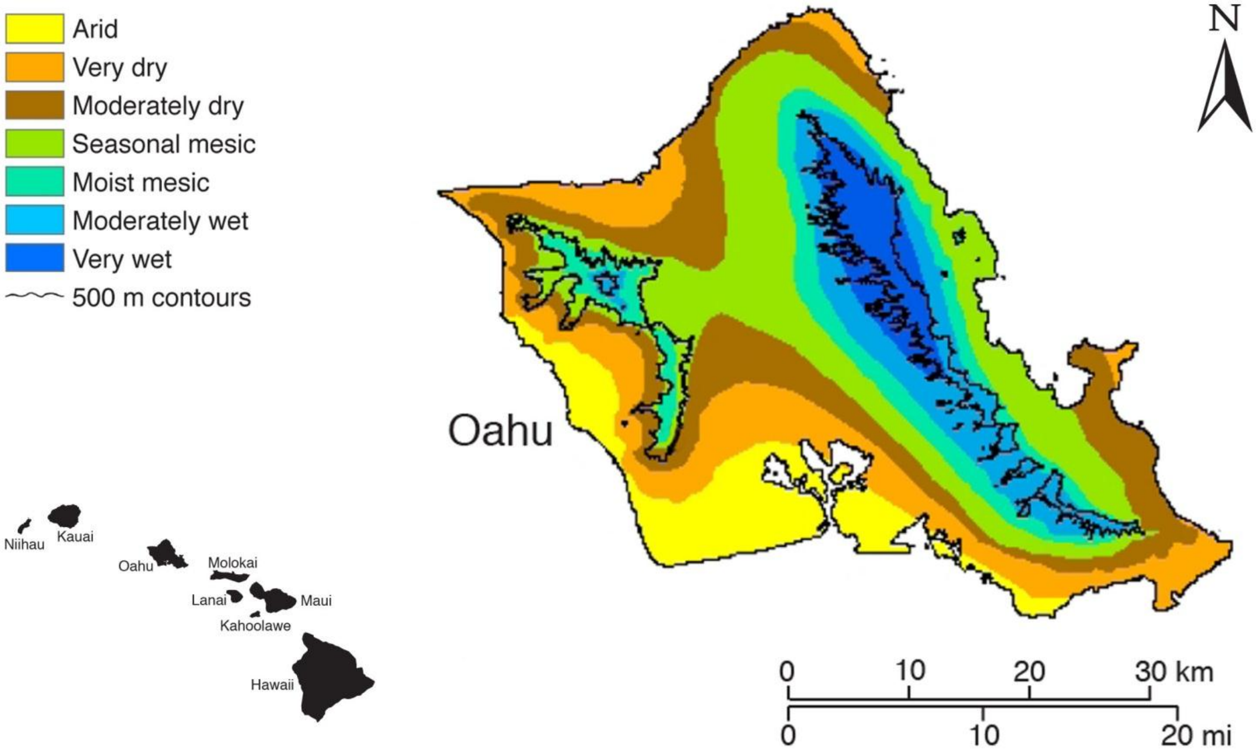

Figure 1: Vegetation zones of Oahu from Price et al. 2008. Arid, very dry, moderately dry, and seasonal mesic zones represent dry forest regions.

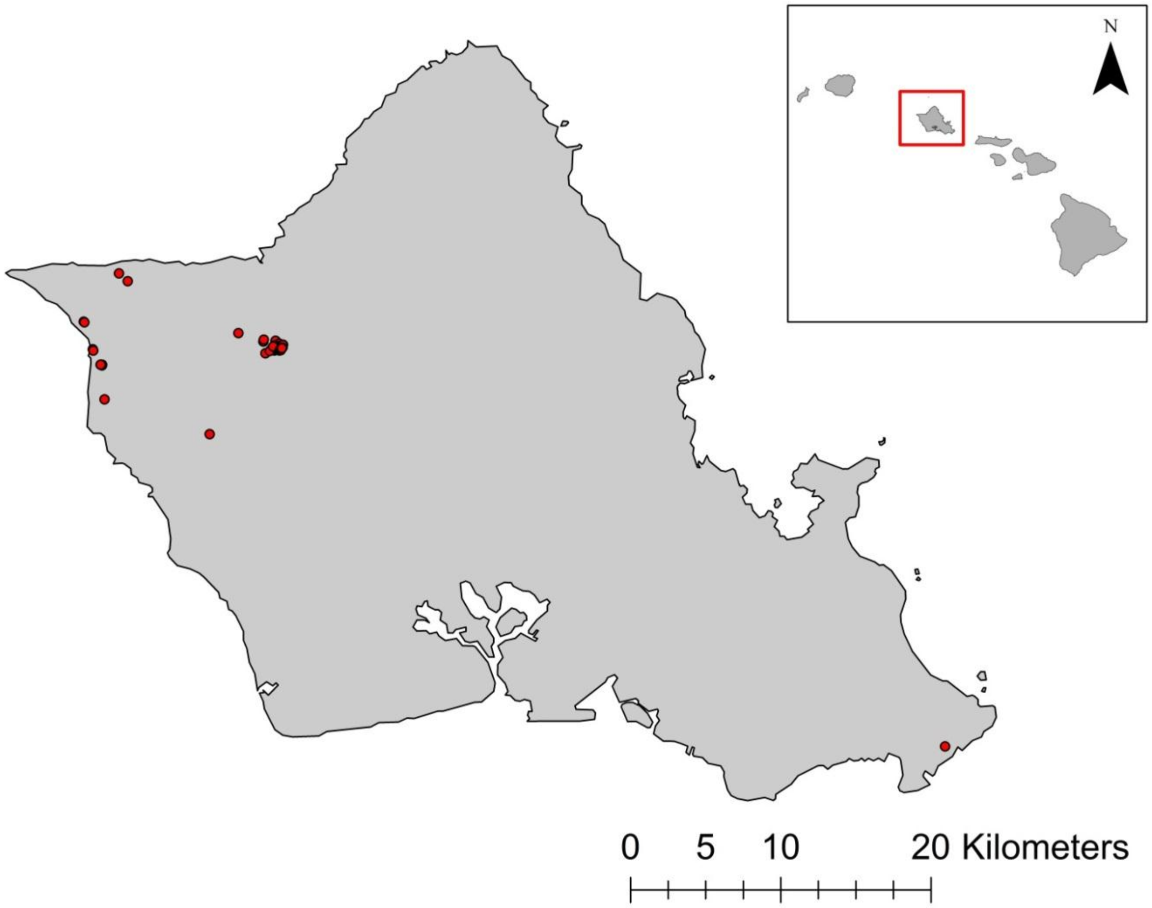

Figure 2: The map displays the only known natural individuals of *H.brackenridgei* on Oahu.

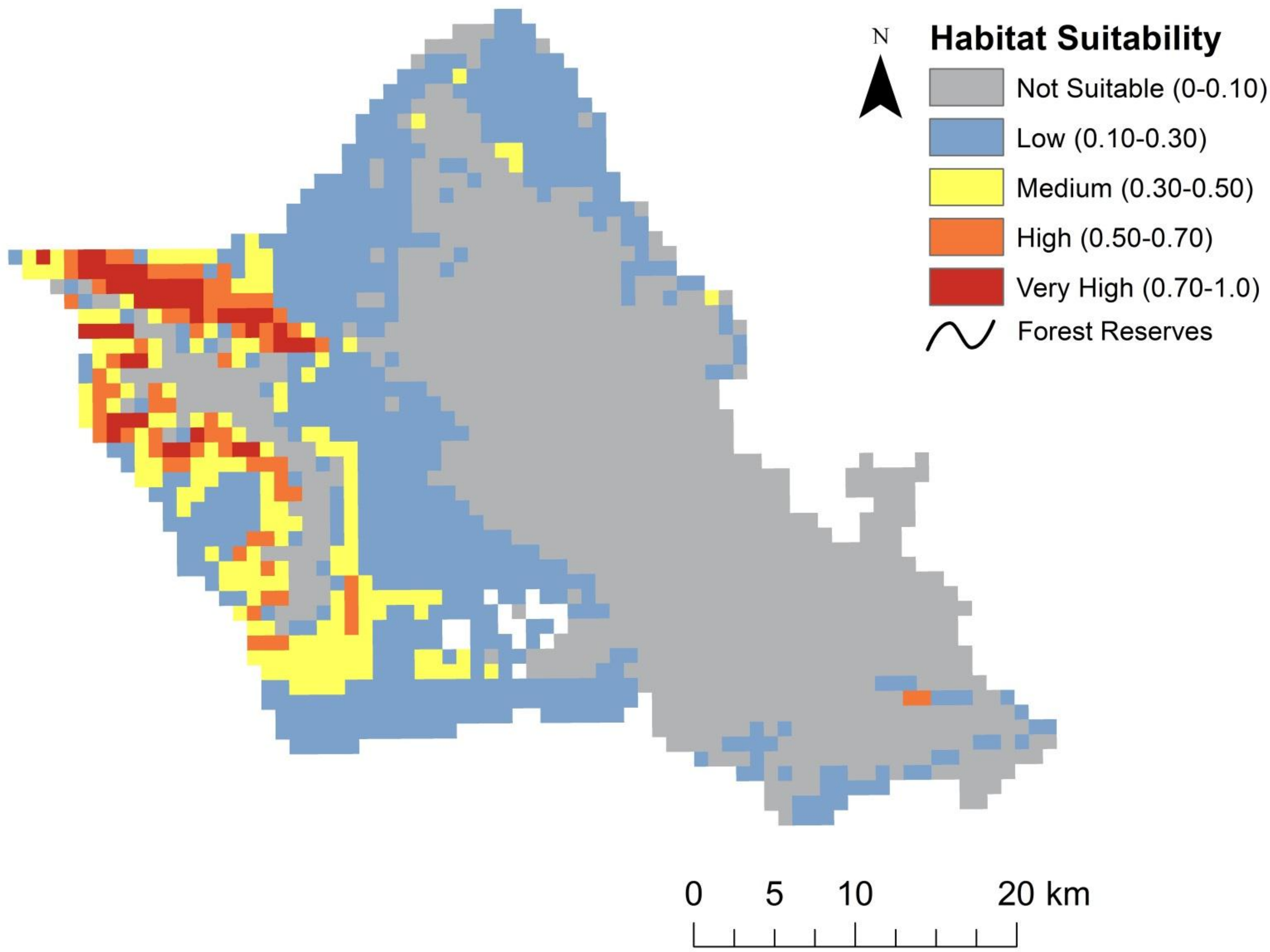

Figure 3: Predicted habitat suitability for *H. brackenridgei* modeled under current conditions.

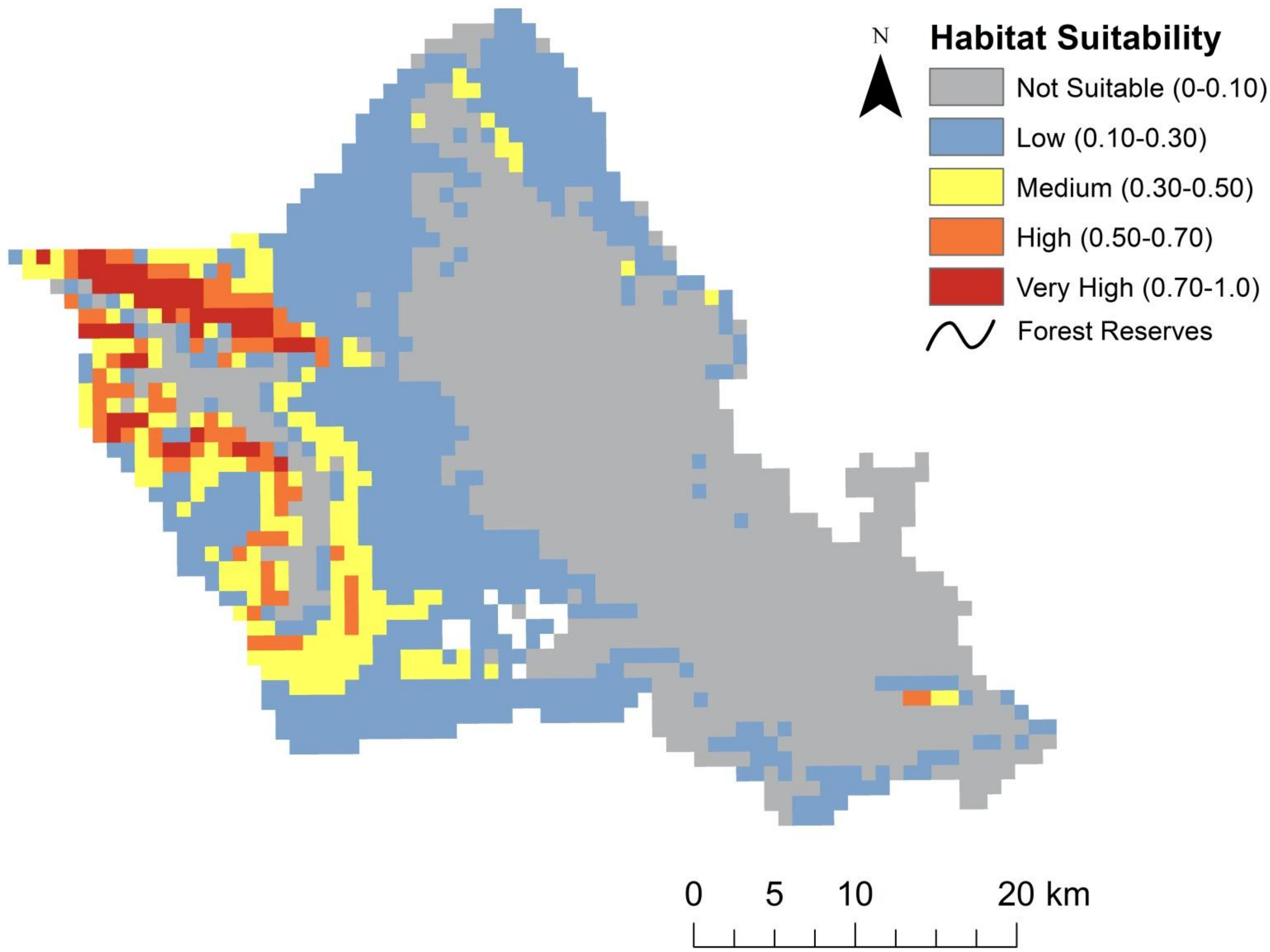

Figure 4: Predicted habitat suitability for *H. brackenridgei* projected onto future B2a emissions scenario conditions.

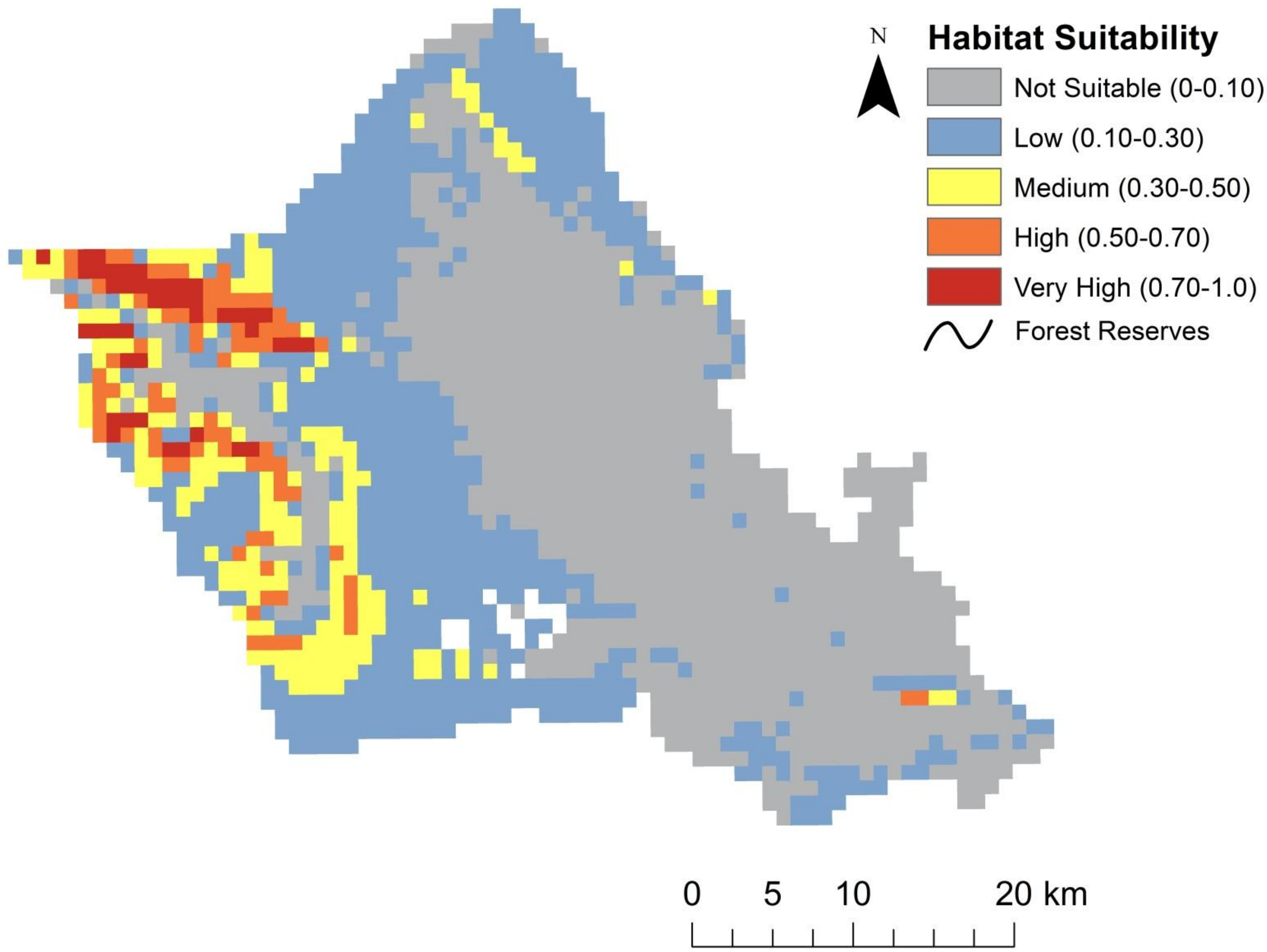

Figure 5: Predicted habitat suitability for *H. brackenridgei* projected onto future A2a emissions scenario conditions.

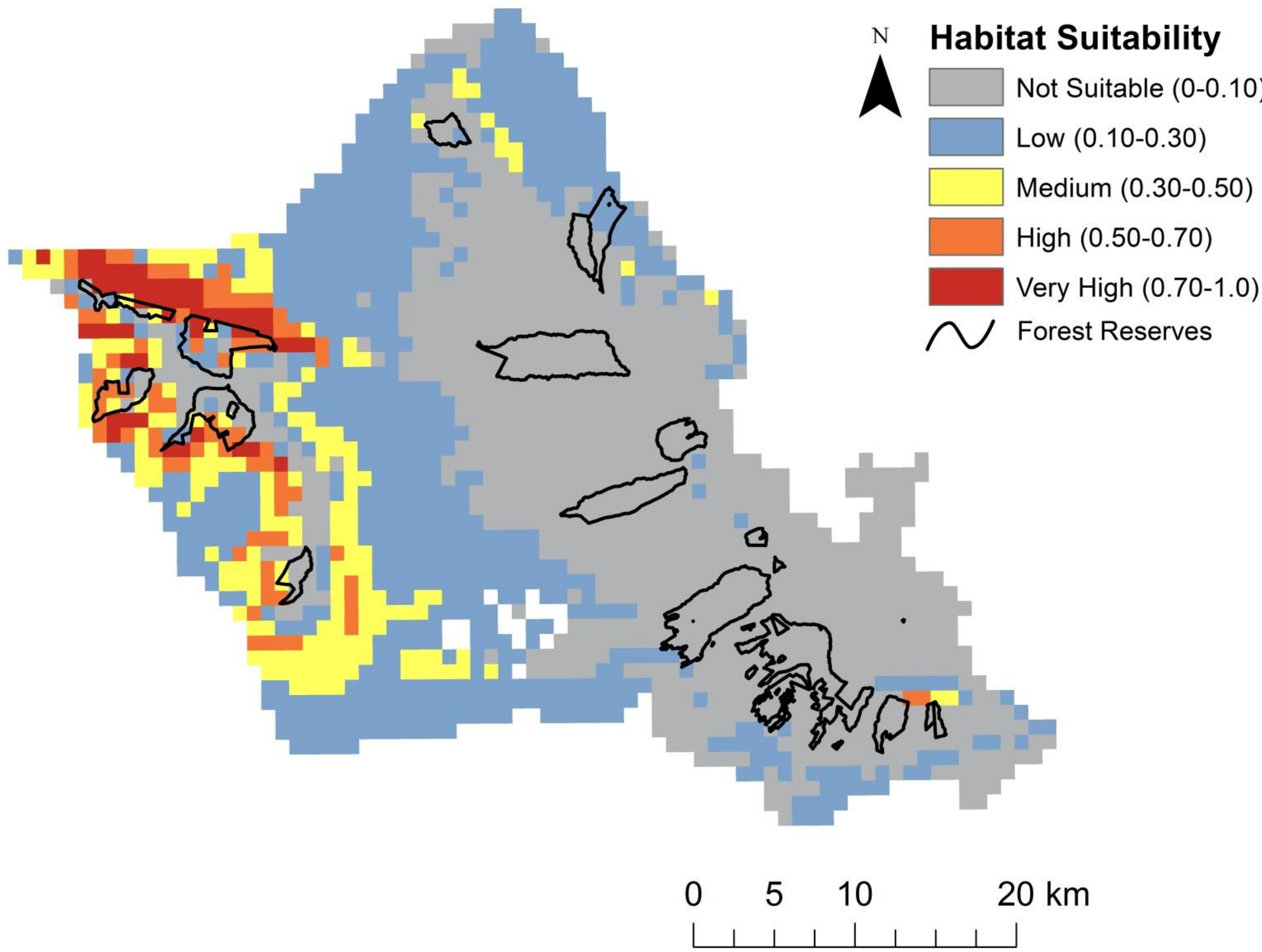

Figure 6: Final robust model considering both current conditions and future A2a projections.

Classified Land Variable	**High/Very High Suitable Areas Within (km^2)**	**Percent of Total High/Very High Areas Within (%)**
Public Land	56	49
Private Land	30	26
Protected Areas	16	14
Currently Managed Areas	12	10
Developed Land	1	0.9
Cultivated Land	2	1.7
Grassland	9	7.8
Evergreen Forest	10	8.7
Scrub/Shrub	92	80
Bare Land	1	0.9

Table 1: High/very high suitable areas (≥ 0.5) within each classified land variable. Additionally, percent of the total high/very high areas (115 km^2) found in each variable is given.

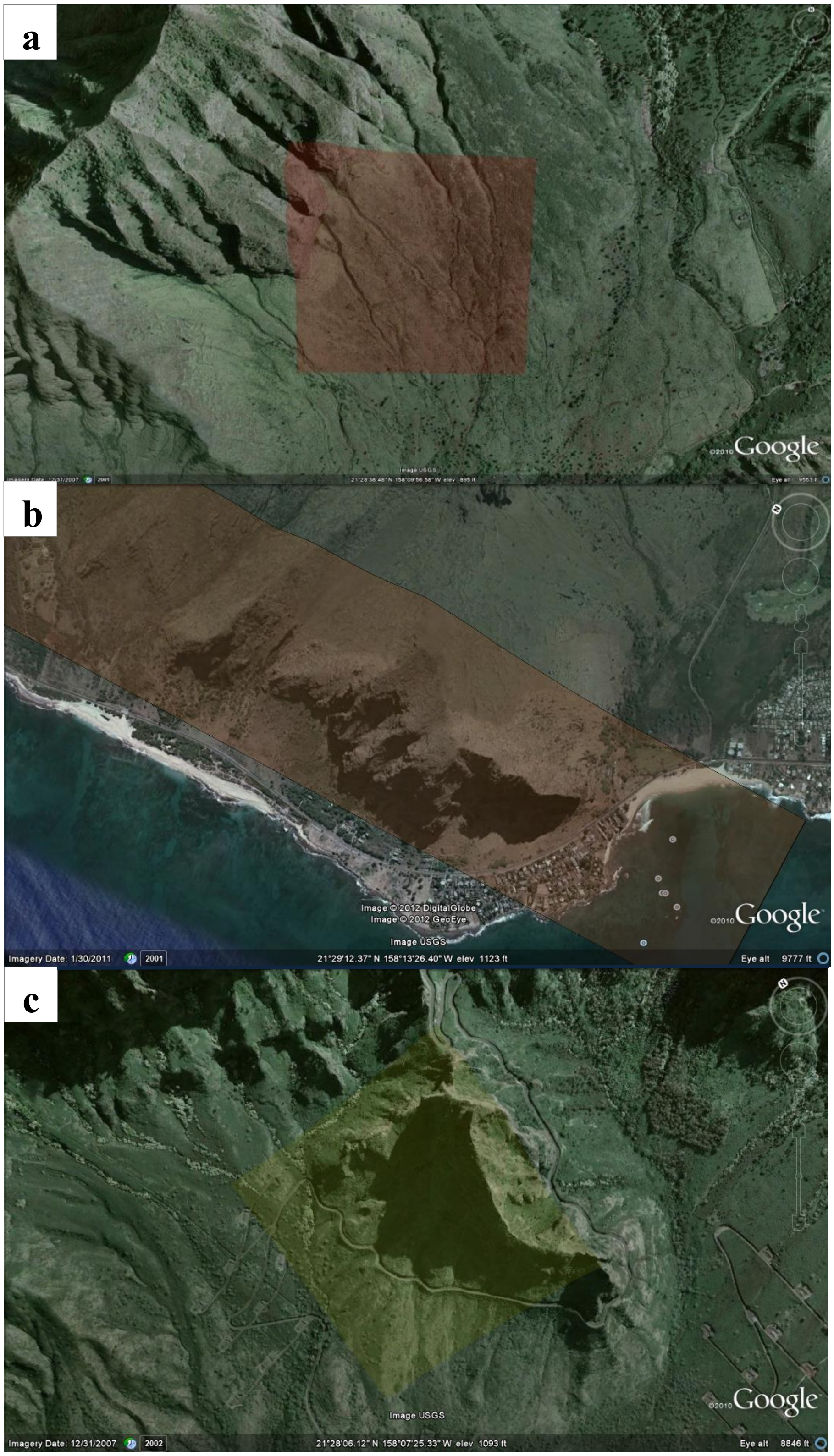

Figure 7: Examples of Google Earth visualization for areas classified as a) very high suitability, b) high suitability, and c) medium suitability

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