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End of Century Climate Predictions and Vulnerability Assessments for Protected Areas and Native Vegetation in the Hawaiian Islands

A thesis submitted in partial satisfaction for the degree

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By

Karina Dutko

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ABSTRACT OF THE THESIS

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for Protected Areas and Native Vegetation in the Hawaiian Islands

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Professor Thomas Gillespie, Chair

The islands of Hawaii consist of an isolated region that may be severely impacted by climate change. Currently, 134 endemic Hawaiian plants are considered extinct and 33% of the native flora are listed as threatened or endangered under the U.S. Endangered Species Act. Many of these species reside in protected areas, yet there have been no comprehensive studies assessing the impacts of climate change on this critical region. Our study examines the future climate vulnerability of native vegetation types in protected areas by utilizing a bioclimatic variables dataset containing baseline and end-of-century (NCAR RCP 8.5) climate projections for the

Hawaiian Islands. We assessed seven native vegetation types (Native Dry Forest, Native Dry Shrub, Native Mesic Forest, Native Mesic Grassland, Native Mesic Shrub, Native Wet Forest, and Native Wet Shrub) using a Forest-Based Classification and Regression approach to determine how distribution ranges of these vegetation types will be impacted by climate change by the end of the century. Our study determined there are statistically significant differences for all pairwise comparisons of the selected native vegetation types in relation to baseline annual precipitation means and annual temperature means, apart from temperature overlap between Native Mesic Grassland and Native Dry Forest classifications. We utilized a multi-category classification approach as well as an individualized single category classification approach to determine potential future vegetation distributions under the NCAR RCP 8.5 climate scenario for the year 2100. Overall, the multi-category classification model had a higher classification accuracy compared to the individualized approach, however the multi-category classification approach results in an exclusionary determination of vegetation type for each pixel, whereas the individualized approach allows for overlap and may be useful for highlighting regions that can sustain two or more vegetation types in the future. Agreement between both methods found that across the entire archipelago, Native Dry Shrub is anticipated to experience the greatest contraction in range followed by Native Wet Forest, while Native Mesic Forest is anticipated to experience the greatest expansion in range, followed by Native Mesic Shrub. Understanding the relationship between future climate and vegetation vulnerability can prove to be vital for land management and conservation efforts as we plan to allocate resources towards areas that are most severely affected by climate change.

The thesis of Karina Dutko is approved.

Elsa Ordway

Park Williams

Michael Shin

Thomas Gillespie, Committee Chair

University of California, Los Angeles

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TABLE OF CONTENTS

Introduction

Climate change is a growing concern as it continues to threaten ecosystems and organisms around the world (Malhi et al. 2020; Trew and Maclean 2021). Increasing temperatures, altered precipitation patterns, higher sea-level, and shifted seasonal timing are just a few of the many variables impacting physiology, phenology, distribution, and composition among ecological systems (Fortini et al. 2017; Malhi et al. 2020; Trew and Maclean 2021). A solution towards addressing this problem is the implementation of climate and vegetation vulnerability assessments (VAs). VAs have been used to synthesize available information to determine the potential impacts of climate change on regions and vegetation of interest (Foden et al. 2019) providing an opportunity to reanalyze, translate, and combine existing and new knowledge within the context of climate change. Typical vulnerability analysis involves three steps, covering the stress to which a system is exposed, its sensitivity, and then its adaptation (Li et al. 2019). However, there have been limited vulnerability assessments and studies on isolated communities that may be more susceptible to climate related extinctions, such as what we see in the case of the Hawaiian Islands.

Climate and Ecosystem Dynamics of the Hawaiian Islands

A series of local and regional dynamic and thermodynamic systems drive precipitation and temperature patterns over the Hawaiian Islands. Nowhere else in the United States are rainfall gradients so steep. Annual rainfall averages 1778 mm but ranges from 127 mm to 11,938 mm (Shlisky 2000). Due to the prevailing trade winds and the topography of the Hawaiian Islands, a characteristic climatic distinction between the “windward” and “leeward” sides exists. The windward sides are characterized by wet climates that support perennial streams and lush vegetation, while the leeward sides are relatively dry (PIRCA 2012). Hawaii's climate also features the important trade wind inversion layer (TWI) that sits at an average altitude of approximately 2,200 m (Cao et al. 2007, Longman et al. 2015). This phenomenon prevents deep convection from occurring, creating arid areas above the elevation of 2,200 m. TWI is present roughly 82% of the time throughout the island chain, although the height of the layer varies daily and spatially across the islands (Cao et al. 2007, Feng and Chen 2001). Previous studies have assessed potential climatic impacts in the near future for the Hawaiian Islands from the years 2026-2035 (Fandrich et al. 2022). These future climate simulations show significant increases in wet season rainfall, of ∼10%–20%, along the windward slopes of Big Island and Maui. Rainfall patterns during the positive Pacific Decadal Oscillation (PDO) phase are projected to reverse in sign, leading to drier conditions, by ∼10%–30%, at many locations. Future climate simulations also suggest daily rainfall extremes will increase, by up to ∼10%–15%, at many locations. Additionally, daily temperature extremes are projected to increase significantly, by up to 1.4 C (Fandrich et al. 2022).

Endemism within the Hawaiian Islands is estimated to be between 86 and 96 percent (Mueller-Dombois 1975, Mueller-Dombois and Fosberg 1998). Conversely, the small size of island land masses supports small populations, increasing extinction rates, and reducing resilience to disturbance (Loope and Mueller-Dombois 1990). The past 200 years have witnessed drastic changes to native Hawaiian ecosystems (Shilsky 2000). Few remnants of natural vegetation are left in the coastal and lowland areas, and currently more than 75 percent of the recognized plant community types remaining in these areas are considered rare (Cuddihy and Stone 1994). Montane and subalpine areas have also been severely impacted by development and non-native plant and animal invasions (Shilsky 2000). Nevertheless, areas still covered with native vegetation can be found in forest reserves, the State Natural Area Reserve System, State Wilderness Preserves, National Parks, and Nature Conservancy Preserves. Given that many of the native plants in the Hawaiian Islands are only able to survive in a niche temperature and precipitation range (Hawaii Cooperative Studies Unit 2013) it is evident that a climate-based vulnerability assessment is essential for conservation efforts in the region.

Regional Climate Model

As climate models continue to improve, the demand for more accurate regional climate projections increases. However, regional climate projections are subject to a high level of uncertainty, especially for the middle and end of the 21st century (Mizukami et al. 2022). A key task for climate modelers is to reduce these uncertainties to yield more accurate climate projections at the regional level. General circulation models offer a sophisticated representation of the general climate system and inform future projections at the global scale. However, GCMs are typically at such a coarse resolution that the models do not reproduce fine-scale spatial patterns of climate in island regions like the Hawaiian Islands. To address this issue, the International Pacific Research Center (IPRC) (Zhang et al. 2016) and the National Center for Atmospheric Research (NCAR) (Xue et al. 2020) have both used dynamical downscaling approaches to generate a higher resolution regional climate model that use pseudo global warming (Kimura 2007) to determine regional model parameters. Both dynamical downscaling products are derived using the Weather Research and Forecasting (WRF) model for historical and future scenarios (Zhang 2012). The latest version of NCAR projections utilizes General Circulation Model averages under future RCP 8.5 emissions (from 2090-2100) to implement change to baseline historical conditions (2002-2012). These simulations from NCAR have been validated and have well documented results that ensure the reliability and integrity of the data

(Xue et al. 2020). These products could be ideal for modelling future climatic and potential native vegetation change for Hawaiian Islands and protected areas. Using the described end of century NCAR models may provide insight into predicted vegetation change due to climate and variation in vegetation modelling approaches, accuracy and results to end of century in the Hawaiian Islands.

Potential Vegetation Type (PVT) Modeling

Species distribution modeling has been used extensively to predict future distributions of species under different climates (Graham et al. 2011), but their map products are often too coarse for fine-scale operational use (Franklin 2013, Keane et al. 2020). Indeed, single species distribution models are subject to biases such as insufficient plot data to fully describe the range of a species, species absence from a plot due to non-climate related disturbances, and seedling establishment facilitated by microclimate rather than macroclimate (Keane et al. 2020). Moreover, because species distribution models are based on single species distributions, projected distributions cannot be combined to reflect changes in vegetation communities, as are often required for many land management tasks. A recently developed alternative approach models Potential Vegetation Types (PVTs) using conventional statistical modeling techniques (such as Random Forest) that uses baseline and future climate variables as predictors. One study obtained over 50% accuracy across 13 mapped PVTs, which were then compared to two previous SDM mapping efforts with over 80% agreement and equivalent accuracy (Keane et al. 2020). Because PVTs represent the biophysical potential of the landscape to support vegetation communities as opposed to the vegetation that currently exists, they can be readily linked to climate forecasts and correlated with other, climate-sensitive ecological processes significant in land management. PVTs have provided critical information for land planning projects and resource management because they represent what may occur (e.g. potential vegetation), as opposed to what currently exists (e.g. existing vegetation) within a given study area. However, to date, PVTs have not been used as a tool for anticipating changing ecosystems and landscapes under climate change.

While Random Forest is often reported to perform well, there are cases where the algorithm has predicted species distributions poorly, often linked to the use of presence-only species data fitted as binary data by using background samples as the second class (Valavi et al. 2021). Additionally, comparisons of various SDM and PVT models show that presence–absence models tend to perform better than presence-only models (Elith et al. 2006). Previous studies have suggested that certain machine-learning modeling methods may outperform others due to their ability to capture complexity and non-linear responses (Elith et al. 2006). Random Forest is an ensemble method that benefits from a structure that grows thousands of trees with a set of randomly selected predictors (Breiman 2001) and has been successfully used in predicting species distributions with limited generalization error (Prasad et al. 2006) whereas MaxEnt is a common approach for modeling species distributions with presence-only species distribution data by finding the probability distribution of maximum entropy subject to a set of constraints that derive from the occurrence data. Recent studies have determined that Random Forest may be a better alternative because it provides the same or similar high predictive accuracy as the MaxEnt model with less computational time and greater stability under general parameters when predicting a species' potential distribution (Zhao et al. 2022). However, there has been limited research on the accuracy of individual iterations of single-class potential vegetation type distributions compared to exclusionary or cohesive multi-type potential vegetation distribution predictions using the random forest algorithm, which our study aims to address. The selection of pseudo-absence or background data is another key consideration in SDM building, given that most species observations concern presence-only data (Ponder et al. 2001). Relevant aspects include the number of pseudo-absences as well as their spatial distribution (i.e., extent and geographic stratification), which may affect model performance as well as the relative importance of predictor variables (Cengic et al. 2020).

Problem Statement

While multiple variations of end-of-century climate data exist (Fortini et al. 2022), there is limited analysis assessing the agreement among future projections of temperature and precipitation between these models. Furthermore, there is limited knowledge on future effects of climate change with respect to native vegetation in protected areas. Our study aims to fill the missing gap in knowledge by conducting an assessment on vegetation vulnerability using future NCAR RCP 8.5 projections as an example to estimate the direction and amount of change we expect of 19 individual bioclimatic variables towards the end of the century (2090 - 2100). In our assessment we define climate change vegetation vulnerability as the relative inability of vegetation types to survive given anticipated temperature and precipitation ranges modeled under future climate change scenarios (Foden 2019). This research had three primary objectives. First, we determined if current native vegetation types in the Hawaiian Islands have distinct climate niches. Second, using the NCAR RCP 8.5 climate scenario we predicted climate change trends for the end of the century and determined which protected areas are expected to have the most severe changes in temperature and precipitation. Third, we modeled potential vegetation distributions using baseline and future climate data using Forest-Based and Boosted Classification and Regression through a single-category prediction method as well as a multi-category prediction method, where we then assessed the accuracy of both outcomes and provided benefits and limitations for both procedures within the context of land use management and conservation.

Methods

Study Area

The Hawaiian Islands include eight major islands: Ni‘ihau, Kaua‘i, O‘ahu, Moloka‘i, Maui, Lāna‘i, Kaho‘olawe, and Hawai‘i. Ni‘ihau is a small, elongated island approximately 29 km in length by 10 km in width and about 180 km^2 in area. The maximum elevation (Pānī‘au) reaches only 381 m. Human disturbance, primarily agriculture and ranching, have drastically changed the vegetation and hydrological parameters of Ni‘ihau, leaving only small native vegetation communities (Gustafson et al. 2014). Kaua‘i is the fourth largest of the main Hawaiian Islands, with an area of 1,430 km^2. The island formed about 4.7 Ma as a single shield volcano. The highest point on Kaua‘i is Kawaikini at 1,598 m, followed by Mount Wai‘ale‘ale near the center of the island at 1,569 m. The windward upper slope of Mount Wai‘ale‘ale is one of the wettest spots on earth, with a mean annual rainfall of 11,700 millimeters (mm) and a record 17,340 mm of rainfall in 1982. Due to its age and relative isolation, Kaua‘i is second among the islands for the highest levels of floristic diversity, and it boasts the highest endemism in the Hawaiian Archipelago (Gustafson et al. 2014). O‘ahu, the third largest Hawaiian island, extends about 71 km in length and 48 km in width, with a total area of 1,545 km^2. Ka‘ala, the highest point on the island, reaches an elevation of 1,220 m. The summit of Ka‘ala is a plateau formed by thick ‘a‘ā lava flows, with poor drainage conditions that produce a montane bog.

The Maui Nui complex of the Hawaiian Islands consists of the islands of Moloka‘i, Maui, Lāna‘i, and Kaho‘olawe, which were connected in the past as a single landmass. The island of

Moloka‘i, the fifth largest in the Hawaiian Islands chain, is approximately 61 km in length and up to 17 km in width, with an area of about 673 km^2. The lower western half of the island is dry, and the soil is heavily denuded due to heavy grazing under past land management practices. The Mo‘omomi Dunes on the northwest coast provide one of the few remaining areas of intact coastal shrub lands in the Hawaiian Islands. Much of the native vegetation on the northern part of East Moloka‘i is relatively intact because of its general inaccessibility to humans and nonnative animals. Lāna‘i is a relatively small island with a total area of 364 km^2. The highest point on the island is Lāna‘ihale, which reaches 1,026 m in elevation. As with other areas of the Islands, heavy grazing of domestic and feral animals in the nineteenth century destroyed much of the native vegetation, eroded soils, and caused major deforestation. Much of the vegetation has never fully recovered, although there have been numerous attempts to revegetate upland areas, mostly with introduced species. Kaho‘olawe is the smallest of the major Hawaiian Islands, with an area of only 116 km^2 and dimensions of about 18 by 11 km. The topography consists of a nearly filled caldera and a rift zone that trends to the southwest, with the highest point being 452 m at the crater of Lua Makika at the summit of Pu‘u Moa‘ulanui. The island is relatively dry because of its low elevation and its position in the rain shadow of Haleakalā. Additionally, overgrazing destroyed most of the vegetation of the island, with subsequent erosion removing much of the topsoil. More than one-quarter of the island has been eroded down to saprolitic hardpan. Maui, the second largest of the Hawaiian Islands, has an area of 1,884 km^2. The larger and younger Haleakalā volcano of East Maui reaches an elevation of 3,055 m. Below the summit lies a massive crater, allowing for the entrance of dense clouds and extensive plant cover.

Hawai‘i, the Big Island, is the largest of the Hawaiian Islands by far, with its total area of 10,433 km^2 comprising almost two thirds of the total land area of the entire State of Hawai‘i.

Mauna Kea, the highest point on the island, reaches 4,205 m in elevation. Measured from its true base in the deep ocean basin some 6,000 m below sea level, Mauna Kea is the tallest mountain in the world, surpassing even Mount Everest.

The native vascular plant flora of the Hawaiian Islands currently includes 1,207 species, comprising 163 ferns and fern allies, 140 monocots, and 904 dicots (Gustafson et al. 2014). A remarkable feature of this flora is a level of endemism that is unparalleled anywhere else in the world. For the total native flora, 88% of species are restricted in distribution to the Hawaiian Islands, with rates of endemism particularly high in the dicots at 93% while monocots and ferns with fern allies each have lower levels of endemism at 73% and 75%. When considering the native Hawaiian flora levels of individual islands, Maui and Kauaʻi are tied in having the greatest number of native species with 629 (Gustafson et al. 2014). Oʻahu is next in diversity with 587 species while Hawaiʻi is significantly lower in richness with a total of 520 species. Molokaʻi has almost as many with 494 species, while Lānaʻi has 362 species (Gustafson et al. 2014) whereas the smaller and relatively arid islands of Niʻihau and Kahoʻolawe have only 99 and 68 native species, respectively.

Climate Data

The product created by the USGS Pacific Islands Ecosystem Research Center features continuous raster data for 19 predictor variables that highlight climatic conditions for the State of Hawaii under both baseline and end-of-century (RCP 4.5 and RCP 8.5) scenarios (Fortini et al. 2022). These bioclimatic variables provide detailed information about annual conditions (annual mean temperature, annual precipitation, annual range in temperature and precipitation), as well as seasonal mean climate conditions (temperature of the coldest and warmest months, precipitation of the wettest and driest quarters) at 250 m resolution utilizing the most up-to-date dynamically downscaled projections based on the Weather Research and Forecasting (WRF) model from the International Pacific Research Center (IPRC) and the National Center for Atmospheric Research (NCAR). Each of these bioclimatic variables are available for one baseline scenario and three projected future scenarios.

Current Climate Data

The bioclimatic variables dataset (Fortini et al. 2022) used 250 m resolution observation-based monthly P_{mean} from the Rainfall Atlas of Hawai'i (Giambelluca et al. 2013) and monthly T_{min}, T_{mean}, and T_{max} from the Climate of Hawai'i (Giambelluca et al. 2014) datasets to replicate closest estimates of baseline temperature and precipitation patterns across the island system. Note that these two datasets have differing historical periods, with the observation-based mean annual precipitation data representing a historical period from 1978–2007 and annual temperature data representing a historical period from 1957-1980. As of today, these precipitation and temperature datasets are considered the most accurate available representation of baseline climate across the islands (Fortini et al. 2022).

Future Climate Data

Future IPRC (2080-2099) and NCAR (2090-2100) projections are available for one simulation under the RCP 4.5 scenario (IPRC) and two simulations under the RCP 8.5 scenario (IPRC and NCAR projections). For the purpose of this study, we only utilized the NCAR RCP 8.5 projection to estimate the changes of the individual bioclimatic variables compared to the baseline scenario to determine the direction and amount of change anticipated for our study area

(Fortini et al. 2022). These fine-scale WRF regional climate simulations by NCAR provide 10-year baseline (2002-2012) and future scenarios (2090-2100, RCP 8.5 only) for the Hawaiian Islands (Xue et al. 2020). The baseline simulation is based on the ERA-Interim global reanalysis data and observed sea surface temperature from the period of October 2002 to September 2012, which was selected to represent the hydrologic seasonality of Hawaii and the availability of ultra-high resolution climate data at 250 m spatial resolution used in this model setup. The future projection uses the Pseudo Global Warming method to implement change based on General Circulation Model averages from 2090 to 2100. This dataset has a major advantage of providing validated hourly rainfall values for the entire study region, which may result in better accuracy compared to other existing simulations. Baseline and future (RCP 8.5 only) projections for P_{mean}, and T_{min}, T_{mean}, and T_{max} variables were provided by NCAR at a monthly gridded scale for the main Hawaiian Islands (Fortini et al. 2022).

Vegetation Data

The Hawaiian Islands have incredible diversity given the small area they occupy, containing 960 flowering plants and 168 ferns and fern allies (Wagner et al. 1990). The Hawai‘i Natural Heritage Program recognizes 150 distinct natural community types (Shlisky 2000), most of which could be classified into nine broad vegetation communities: tropical coastal vegetation, lowland grasslands and savanna, montane moist forests, lowland rain forest, montane wet forests and bogs, subalpine vegetation, alpine vegetation, and montane dry forests (McNab and Avers 1994). Our study utilized the classification system from the Carbon Assessment of Hawaii Land Cover Map featuring twenty-seven General Land Cover Types (Figure 1), seven of which compose the existing native vegetation landscape (Native Dry Forest, Native Dry Shrub, Native

Mesic Forest, Native Mesic Grassland, Native Mesic Shrub, Native Wet Forest, and Native Wet Shrub) (Jacobi et al. 2017). Non-Native vegetation was grouped together and excluded from this analysis as the purpose of this study is only to highlight suitable distribution ranges under a changing climate, and cannot consider competition between resources in our machine learning algorithm as invasive species are expected to compete and dominate in areas that are considered suitable ranges under a future climate.

Although there have been many maps produced that depict vegetation for the State of Hawaiʻi, only a few of these display land cover for all of the main Hawaiian Islands, and most of those that were created before the year 2000 have very generalized units or are somewhat inaccurate as a result of more recent land use changes or poor resolution (both spatial and spectral) in the imagery that was used to produce the map. The Carbon Assessment of Hawaii (CAH) Land Cover Map (Jacobi et al. 2017) was utilized to provide high resolution (30 m) land cover maps with a detailed hierarchical vegetation group classification system (Figure 1). Base maps for this newly compiled CAH land-cover map included vegetation units and boundaries from the HIGAP land cover map (Gon et al. 2006), land-use units from the 2005 NOAA C-CAP map (NOAA National Ocean Service Coastal Services Center 2012), the "bare" (<5 percent vegetation cover) map unit from the Hawaiʻi LANDFIRE map (Rollins 2009, U.S. Geological Survey 2009), and data on the distribution of managed tree plantations for the main Hawaiian Islands on both state lands (Yoshiko Akashi, Hawaiʻi Division of Forestry and Wildlife, unpublished data) and private lands (Nicholas Koch, Forest Solutions Inc., unpublished data). All spatial files were projected in UTM Zone 4 using the NAD83 datum. The HIGAP, NOAA C-CAP, and LANDFIRE maps were all based on LANDSAT TM imagery with 30 by 30 m (900 m^2) pixels. Each land-use or land-cover data layer was reviewed for accuracy of its selected units by comparing the mapped units to more recent high-resolution WorldView 2 digital satellite imagery collected by DigitalGlobe in 2010 (<2 m pixel size) and very high-resolution imagery from Pictometry Online (POL; Pictometery International 2014), which were also projected in UTM Zone 4 NAD 83. Where differences were found between the original mapped land-use and land-cover units and the high-resolution imagery, corrections were made to the original raster maps by reclassifying pixels to their correct values using raster editing software. The mapped units for the CAH land-cover map are linked to the alliance and association levels of the revised National Vegetation Classification (rUSNVC) which is based on the National Vegetation Classification Standard that was formally adopted by the Federal Geographic Data Committee (FGDC) in 2008 (FGDC 2008). These units also correspond with NatureServe's Terrestrial Ecological Systems Classification (NatureServe 2010, 2011). However, one major difference between the various CAH land-cover classification levels and the rUSNVC classification is that in the CAH land-cover map we did not separate the units into lowland, montane, and alpine units.

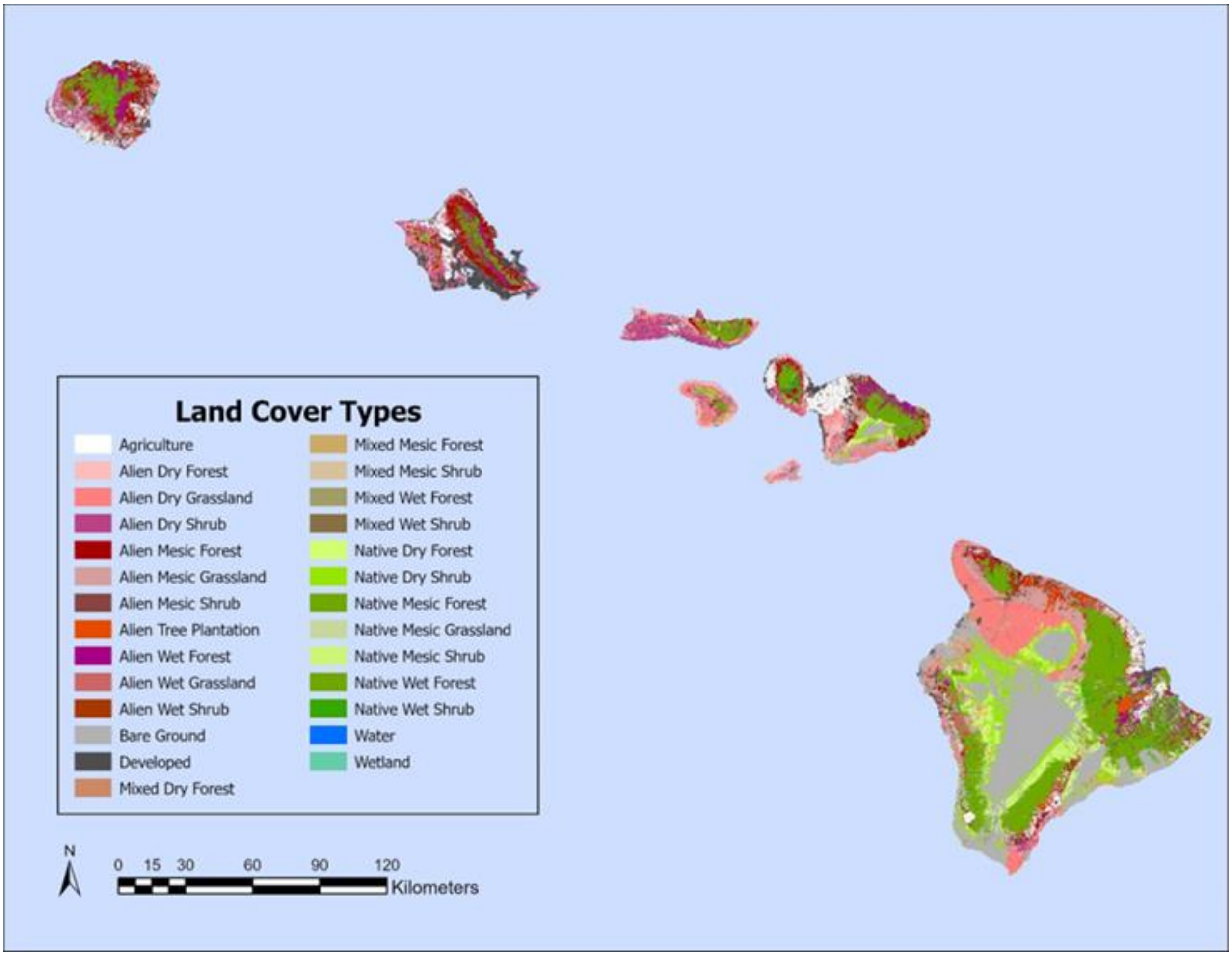

Figure 1: Depicts general land cover types and biomes that represent land use and potential vegetation zones (Carbon Assessment of Hawaii Land Cover Map 2017).

Protected Areas

The Hawaiian Islands are home to large, protected areas which help make up the over 8,000 km^2 of conservation lands managed by federal, state, local and private agencies (State of Hawaii, Office of Planning and Development 2022). These include national parks, wildlife refuges, forest reserves, and private land holdings. For the purposes of our study, we will refer to The International Union for Conservation of Nature (IUCN) official definition of a protected area, defined as “a clearly defined geographical space, recognized, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values” (IUCN Definition 2008). The ranges for projected areas of interest are set to fall within 308 zones that cover the natural terrain of the Hawaiian island chain. This results in a combined total area of 6,973 km^2 of protected regions (Figure 2).

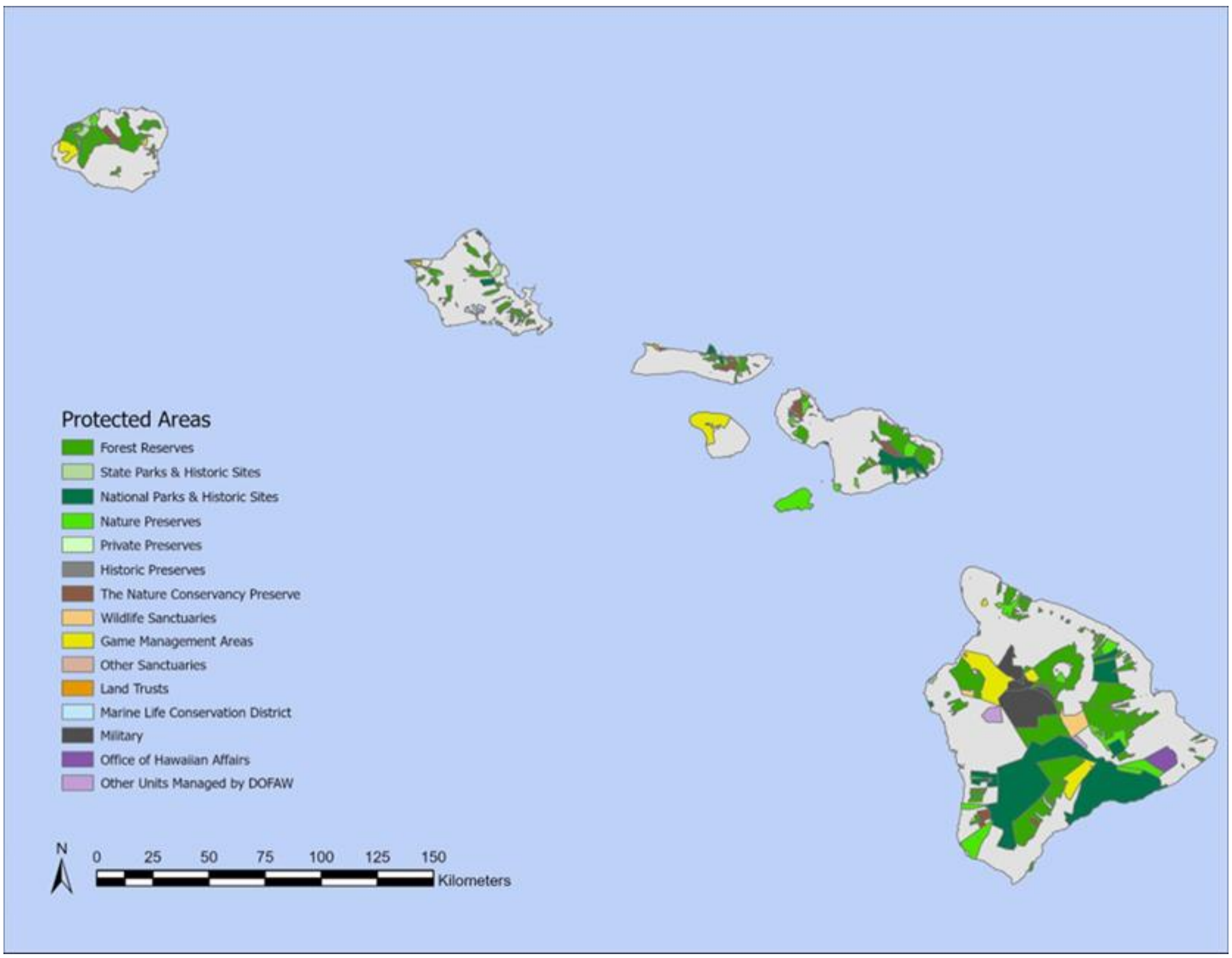

Figure 2: Recognized protected area classifications (Department of Fish and Wildlife 2023).

Statistical Tests on Climate Ranges by Native Vegetation Type

Species Distribution Models have accurately modeled climate envelopes or climate niches using a combination of historical and current climate data to monitor potential ranges for individual species, however there is limited knowledge on determining accurate climate ranges by vegetation type. Therefore, it is critical to run a series of statistical tests to determine if the native vegetation types within our study region have defined climate envelopes using available historical precipitation and temperature data. This study will be the first of its kind to implement potential vegetation type models as a tool for anticipating changing ecosystems and landscapes under climate change towards the end of the century, and by determining these climate envelopes using historical temperature and precipitation data as a baseline measure, we are able to set a standardized methodology for predicting future potential vegetation types in any region that is anticipating severe climate impacts.

Our first research objective was to assess if specific precipitation and temperature parameters resulted in clearly distinguishable climate envelopes or climate niches within seven native vegetation types. A one-way Analysis of Variance (ANOVA) test was run on each native vegetation type to determine if there is a difference in means between groups regarding the annual temperature and annual precipitation variables. This is a critical step prior to running a Forest Based and Boosted Classification and Regression because significant difference of climate variable means between vegetation types will result in a more accurate future distribution model. The null hypothesis (H_0) of the ANOVA states there is no difference in means, and the alternative hypothesis (H_a) states that the means of each group are different from one another. The one-way ANOVA test outputs the degrees of freedom for the independent variable, the degrees of freedom for the residuals, the sum of squares, the mean of the sum of squares (calculated by dividing the sum of squares by the degrees of freedom for each parameter), the F value, and the p value of the F statistic. The larger the F value, the more likely it is that the variation caused by the independent variable is real and not due to chance whereas the p value of the F statistic determines how likely it is that the F value calculated from the test would have occurred if the null hypothesis of no difference among group means were true.

Zonal Statistics

To conduct our assessment on temperature and precipitation changes towards the end of the century, we utilized the bioclimatic variables "Annual Mean Temperature" (Band 1) and "Annual Precipitation" (Band 12) for the baseline and NCAR RCP 8.5 climate scenarios of the Bioclimatic Variables dataset from Fortini et al. (2022) (Table 1). The baseline climate model was then subtracted from the annual mean temperature layer and annual precipitation layer of the RCP 8.5 NCAR projections using the Raster Calculator (Spatial Analyst) in ArcGIS Pro 3.1.

Bioclimatic Variable	**Description**
1	Annual mean temperature
2	Mean diurnal range (Mean of monthly max temperature - min temperature)
3	Isothermality (Mean diurnal range/ temperature annual range)
4	Temperature seasonality (Standard deviation of monthly mean temperature)
5	Max temperature of warmest month
6	Min temperature of coldest month
7	Temperature annual range (Max temperature of warmest month - min temperature of coldest month)
8	Mean temperature of wettest quarter
9	Mean temperature of driest quarter
10	Mean temperature of warmest quarter
11	Mean temperature of coldest quarter
12	Annual precipitation
13	Precipitation of wettest month
14	Precipitation of driest month

15	Precipitation seasonality (Coefficient of variation for monthly precipitation)
16	Precipitation of wettest quarter
17	Precipitation of driest quarter
18	Precipitation of warmest quarter
19	Precipitation of coldest quarter

Table 1: Bioclimatic Variables 1-19 from Fortini et al. (2022)

For each of the protected areas, Zonal Statistics (Spatial Analyst) was used in ArcGIS Pro 3.1 with the value raster of Band 1 and Band 12 of the future climate model calculated in the temperature and precipitation assessment. This resulted in calculations for the minimum value, maximum value, range, mean, standard deviation, sum, median, and 90th percentile for expected change in temperature and expected change in precipitation for each individual polygon in our protected areas of interest given each future climate scenario.

Calculating Native Vegetation Distribution Models and Change

Comparisons of various SDM and PVT models show that presence–absence models tend to perform better than presence-only models (Elith et al. 2006). Thus, presence–absence models are increasingly used when only presence data is available, by creating artificial absence data (also known as pseudo-absences). We selected randomized point locations of native vegetation types by using the Raster to Point tool in ArcGIS Pro to extract raster values to points for each land cover type. We then used the Subset Features tool to select a random subset of 10,000 points for each Native Vegetation type (except for Native Mesic Grassland, which only contained 4,831 points), 10,000 points for bare ground, and 20,000 points for all other combined categories that did not represent native vegetation or bare ground. This finalized subset was used as the presence data input in lieu of species, which also served as pseudo absence data for each native vegetation type. Current native vegetation distribution models were created using a random forests (RF) approach, implemented in the Forest-based and Boosted Classification and Regression (Spatial Statistics) tool in ArcGIS Pro 3.2. Variables used to create the current explanatory raster inputs include elevation (USGS), soil order from the Hawaii Soil Atlas, mean annual temperature, mean annual precipitation, precipitation seasonality (Coefficient of variation for monthly precipitation), and temperature seasonality (standard deviation * 100).

This RF model was then used to predict future distributions of native vegetation classes across the study area. Here, we used the biophysical gradient under the NCAR RCP 8.5 future climate scenario as the predictor variables in the RF model to predict and map seven native vegetation class distributions using an individualized approach as well as a multi-category classification approach. It is important to note that we are not predicting migrations of native vegetation classes themselves under future climates; rather, we are predicting differences in spatial patterning of the climatic conditions where current native vegetation assemblages may exist under future climates. As stated previously, non-native vegetation was grouped together and excluded from this analysis under the category "Other Non-Native Vegetation" because the primary purpose of our study is only to highlight suitable distribution ranges under a changing climate, and due to the complexity of integrating multiple variables and compromising accuracy we cannot consider competition between resources in our machine learning algorithm as invasive species are naturally expected to outcompete and dominate in areas that are considered suitable for native vegetation. Therefore, practical applications of this study must take additional conservation measures to account for the spread of invasive species that may pose as an additional threat to native vegetation.

The individualized approach consists of running the Random Forest model using presence and absence points for each native vegetation type with separate runs which results in seven predicted outputs of baseline and future projections for each category. To create an accurate visual of contraction and expansion of range for each species, the baseline and NCAR RCP 8.5 Random Forest predicted outputs were reclassified and the sum of the values was calculated using the Raster Calculator, creating a new finalized raster output for each vegetation type. Prior to adding the baseline and NCAR random forest outputs for each vegetation type, the baseline value was reclassified to “0” for “Absent” vegetation type, and “1” for “Present” vegetation type, while the NCAR future climate prediction output was reclassified to a value of “0” for “Absent” vegetation type and “2” for present vegetation type. When added, a raster value of 0 represents an absence of vegetation in both climate scenarios. A raster value of 1 represents an absence in the future NCAR scenario while maintaining a presence in the baseline, also known as a contraction of range. A raster value of 2 represents an absence in the baseline climate scenario and presence of vegetation in the future NCAR RCP 8.5 scenario, also seen as an expansion of range. Finally, a raster value of 3 represents presence of vegetation in both baseline and NCAR climate scenarios, meaning there is no anticipated change in existing vegetation range. Figure 3 outlines the raster reclassification and addition process.

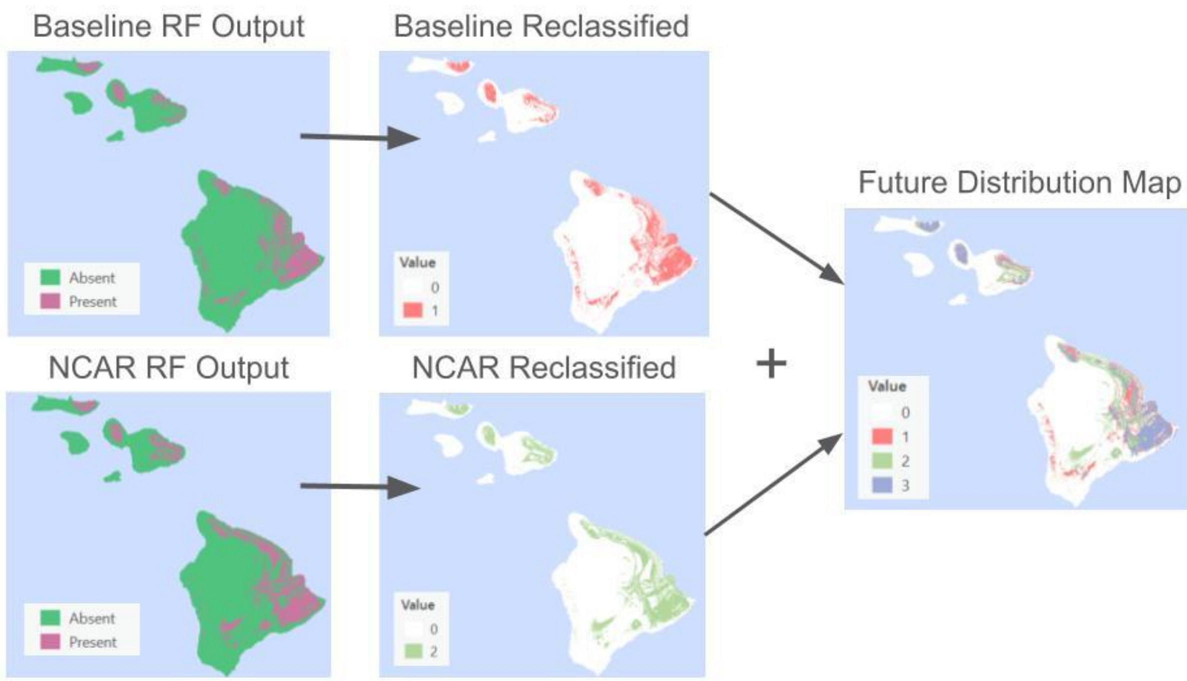

Figure 3: Depiction of Random Forest Vegetation Distributions and Raster Output Calculations.

In addition to producing individualized outputs for each potential future vegetation range, the Forest Based and Boosted Classification and Regression tool (ArcGIS Pro 3.2) was utilized to create a multi-category assessment where presence only data was provided as an input along with the same parameters outlined in the individualized approach. Training features included bare ground, native dry forest, native dry shrub, native mesic forest, native mesic grassland, native mesic shrub, native wet forest, native wet shrub, and “other”. All categories except for “other” and “native mesic grassland” consist of a random sample of 10,000 points extracted from the Carbon Assessment of Hawaii Land Cover Map (Jacobi et al. 2017). The “other” category consists of a random sample of 20,000 points from all categories outside of the seven native vegetation types and bare ground features, and the “native mesic grassland” category contains 4,831 points due to scarcity.

Results

Native Vegetation and Climatic Niche

The outputs of our one-way ANOVA suggest that for both Annual Precipitation and Annual Temperature, the large F value and small p value of the F statistic indicate that the variation in temperature and precipitation (Table 2) can be predicted by the native vegetation type, and we are able to reject the null hypothesis (H_0) of the ANOVA of no difference in means.

Native Vegetation Types	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**p of F Statistic**
Annual Precipitation	6	1.08 e 13	1.80 e 12	1091560	<0.001
Annual Temperature	6	11983486	1997248	183919	<0.001

Table 2: ANOVA output for Annual Precipitation and Annual Temperature

We then checked for homoscedasticity, or homogeneity of variances, which is an assumption of equal or similar variances in different groups being compared. This is an important assumption of parametric statistical tests because they are sensitive to any dissimilarities. Uneven variances in samples result in biased and skewed test results. The diagnostic plots in Figure 4 show the unexplained variance (residuals) across the range of the observed data. The red line representing the mean of the residuals is horizontal and centered on zero, meaning that there are no large outliers that would cause research bias in the model. The normal Q-Q plot plots a regression between the theoretical residuals of a perfectly homoscedastic model and the actual residuals of the model, and in the case of this model we only encounter minor deviation from the ideal slope of 1. From these diagnostic plots we can say that the model fits the assumption of homoscedasticity.

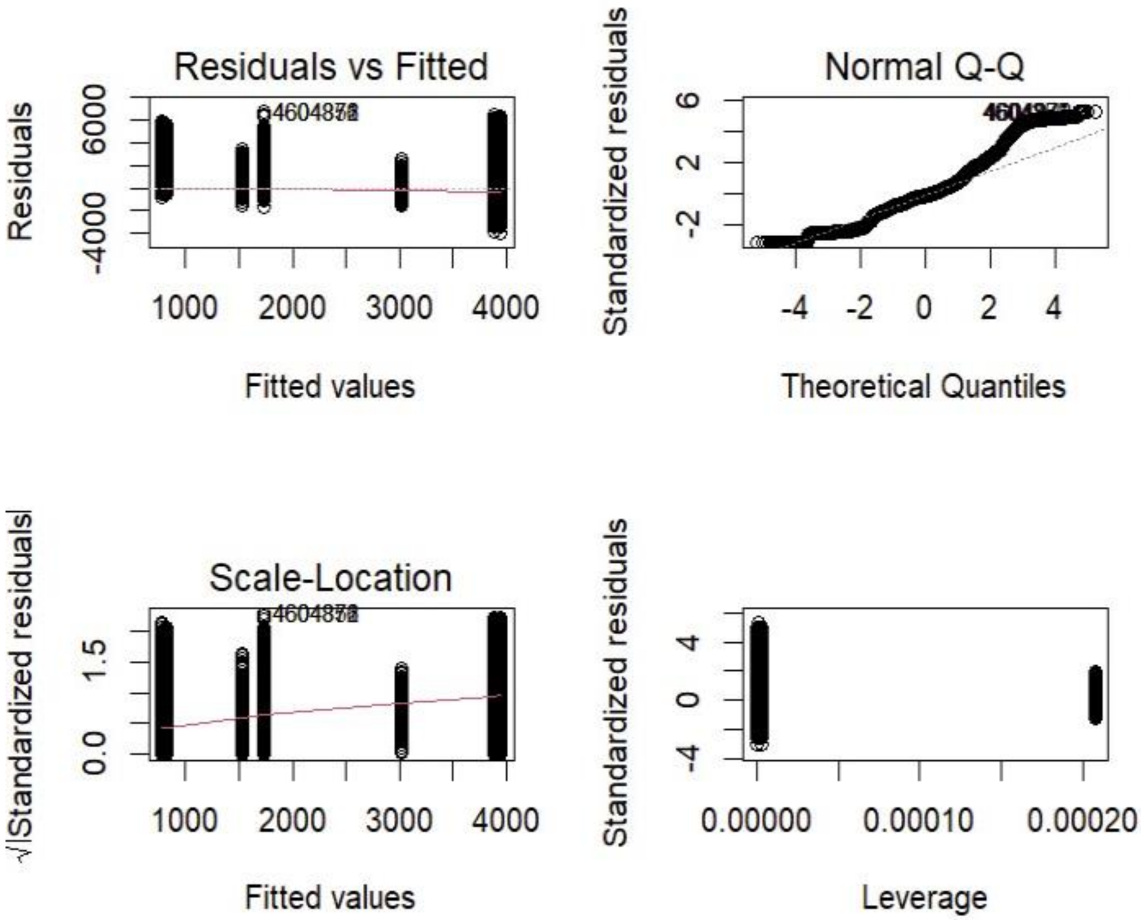

Figure 4: Diagnostic Plots to Determine Homoscedasticity between Grouped Native Vegetation Types. These results conform that there is no unexplained variance (residuals) across the range of the observed data, and our model of temperature and precipitation by group meets the assumption of homoscedasticity.

While ANOVA determines if there were differences amongst group means, it does not determine what those differences were. We ran Tukey's Honestly Significant Difference

(Tukey's HSD) post-hoc test to determine the difference in means for pairwise comparisons using the variables of Annual Precipitation and Annual Temperature for each vegetation group. Table 3 reflects the output of these tests.

Tukey Multiple Comparisons of Means 95% Family-Wise Confidence Level	**Annual Temperature C**		**Annual Precipitation mm**	
Native Vegetation Types	**Difference**	**p value**	**Difference**	**p value**
Native Dry Shrub vs Native Dry Forest	1.91	<0.001	-40.40	<0.001
Native Mesic Forest vs Native Dry Forest	3.75	<0.001	904.62	<0.001
Native Mesic Grassland vs Native Dry Forest	0.13	0.10	2192.11	<0.001
Native Mesic Shrub vs Native Dry Forest	2.03	<0.001	713.09	<0.001
Native Wet Forest vs Native Dry Forest	4.45	<0.001	3119.91	<0.001
Native Wet Shrub vs Native Dry Forest	5.73	<0.001	3056.88	<0.001
Native Mesic Forest vs Native Dry Shrub	1.84	<0.001	945.01	<0.001
Native Mesic Grassland vs Native Dry Shrub	-1.78	<0.001	2232.50	<0.001
Native Mesic Shrub vs Native Dry Shrub	0.13	<0.001	753.48	<0.001
Native Wet Forest vs Native Dry Shrub	2.54	<0.001	3160.30	<0.001
Native Wet Shrub vs Native Dry Shrub	3.83	<0.001	3097.28	<0.001
Native Mesic Grassland vs Native Mesic Forest	-3.62	<0.001	1287.49	<0.001
Native Mesic Shrub vs Native Mesic Forest	-1.71	<0.001	-191.53	<0.001
Native Wet Forest vs Native Mesic Forest	0.70	<0.001	2215.29	<0.001
Native Wet Shrub vs Native Mesic Forest	1.99	<0.001	2152.27	<0.001
Native Mesic Shrub vs Native Mesic Grassland	1.91	<0.001	-1479.02	<0.001
Native Wet Forest vs Native Mesic Grassland	4.31	<0.001	927.80	<0.001
Native Wet Shrub vs Native Mesic Grassland	5.60	<0.001	864.78	<0.001
Native Wet Forest vs Native Mesic Shrub	2.41	<0.001	2406.82	<0.001
Native Wet Shrub vs Native Mesic Shrub	3.70	<0.001	2343.79	<0.001
Native Wet Shrub vs Native Wet Forest	1.29	<0.001	-63.02	<0.001

Table 3: Output of Tukey's HSD for Annual Temperature and Annual Precipitation by Group.

The Tukey's HSD test runs multiple comparisons of means at the 95% family-wise confidence level. The "difference" column highlights the difference between vegetation types for the tested variable within the 95% confidence variable for each pairwise comparison. From the post-hoc test results, we see that there were statistically significant differences ($p < 0.05$) for all pairwise comparisons of vegetation type in relation to annual precipitation means. This was also true for most of the comparisons of vegetation type in relation to temperature (Table 3). However, the comparison of Annual Temperature means between Native Mesic Grassland and Native Dry Forest resulted in a p value of 0.10, which was not a statistically significant difference in means.

Predicted Climate Change in Protected Areas

When comparing baseline and future climate scenarios, NCAR RCP 8.5 predicted a minimum of 3.21 °C increase and maximum of 4.79 °C increase across all regions of the Hawaiian Islands (Appendix Figure 2A). To calculate percent change for temperature and precipitation, the equation (Future Value – Baseline Value) / Baseline Value was implemented. For some precipitation statistics where the difference between minimum values are 0, calculations were conducted with the assumption that a minimum of 1mm of annual rainfall would occur in every area. With regards to precipitation, NCAR RCP 8.5 predicted a maximum decrease of 747 mm and maximum increase of 1,408 mm from the baseline of 0 mm of anticipated change. The majority of extreme temperature changes are expected to occur on the islands of Hawai'i (The Big Island) and Maui.

Our study assessed 157 protected areas across the Hawaiian Islands (Figure 2). Our findings suggest that the highest maximum projected temperature increase includes Mauna Kea Ice Age Natural Reserve, Hawaii Volcanoes National Park, Kapapala Forest Reserve, Mauna Kea Forest Reserve, Mauna Loa Forest Reserve, Alpine Wildlife Sanctuary, Haleakala National Park, Kula Forest Reserve, and Kahikinui Forest Reserve. The highest mean temperature increase was found to occur in Mauna Kea Ice Age Natural Reserve, Mauna Loa Forest Reserve, Alpine Wildlife Sanctuary, Keauhou Cooperative Nene Sanctuary, Kipuka Ainahou Nene Sanctuary, and Kaonoulu Ranch Cooperative Game Management Area. Table 4 highlights these anticipated temperature increases.

Island	**Protected Area Name**	**Difference in MAX Anticipated Temperature °C (%)**	**Difference in MEAN Anticipated Temperature °C (%)**
Hawaii	Mauna Kea Ice Age Natural Reserve	4.78 (63%)	4.68 (76%)
Hawaii	Hawaii Volcanoes National Park	4.78 (20%)	4.05 (29%)
Hawaii	Kapapala Forest Reserve	4.76 (32%)	4.21 (40%)
Hawaii	Mauna Kea Forest Reserve	4.76 (34%)	4.42 (51%)
Hawaii	Mauna Loa Forest Reserve	4.72 (41%)	4.50 (53%)
Maui	Alpine Wildlife Sanctuary	4.63 (53%)	4.62 (57%)
Maui	Haleakala National Park	4.62 (19%)	4.04 (31%)
Maui	Kula Forest Reserve	4.61 (31%)	4.28 (38%)
Maui	Kahikinui Forest Reserve	4.61 (24%)	4.12 (32%)
Hawaii	Keauhou Cooperative Nene Sanctuary	4.52 (37%)	4.39 (44%)

Table 4: Highlights of the top ten most severe anticipated temperature increases of protected areas based on maximum and mean anticipated temperature increase from NCAR RCP 8.5.

The islands of Hawai'i and Maui are also expected to endure the most extreme precipitation changes (Table 4, Table 5). The NCAR RCP 8.5 projection suggests the most severe decrease in annual precipitation is expected to affect Haleakala National Park, Kau Forest Reserve, Hana Forest Reserve, Hawaii Volcanoes National Park, and Koolau Forest Reserve. In addition, the lowest mean precipitation values were found to affect Kau Forest Reserve, Kaumahina State Wayside, Hanawi Natural Area Reserve, and Kipahulu Forest Reserve. Alternatively, regions with the highest mean precipitation values include sections of Hamakua Forest Reserve and Manowaialee Forest Reserve. Kohala Forest Reserve and Puu O Umi Natural Area Reserve also experienced some of the highest maximum precipitation values. Table 5 summarizes the most affected protected areas in terms of precipitation.

Island	**Protected Area Name**	**Difference in MINIMUM Anticipated Precipitation Change mm/year**	**Difference in MAXIMUM Anticipated Precipitation Change mm/year**	**MEAN Anticipated Precipitation Change mm/year**
Maui	Haleakala National Park	-747	+324	-49 (2% decrease)
Hawaii	Kau Forest Reserve	-691	+181	-337 (14% decrease)
Maui	Hana Forest Reserve	-680	+430	+2 (~0% change)
Hawaii	Hawaii Volcanoes National Park	-650	+904	+9 (~0% change)
Maui	Koolau Forest Reserve	-641	+312	-111 (2% decrease)
Maui	Hanawi Natural Area Reserve	-594	+102	-251 (3% decrease)
Maui	Kipahulu Forest Reserve	-371	-38	-246 (7% decrease)
Maui	Hamakua Forest Reserve	+1277	+1397	1345 (60% increase)

Hawaii	Manowaialee Forest Reserve	+1033	+1364	1180 (35% increase)
Hawaii	Kohala Forest Reserve	+285	+1201	685 (24% increase)

Table 5: Highlights of most severe anticipated precipitation increases/decreases of protected areas sorted by absolute values in precipitation change (mm/year) between historical conditions (2002-2012) and end of century NCAR RCP 8.5 projections (2090-2100).

Protected Area Name	**% Min**	**% Max**	**% Mean**
Kona Hema Preserve (Nature Conservancy)	-27.66	-4.48	-20.45
Kapapala Forest Reserve	-96.50	5.73	-16.22
Kau Forest Reserve	-46.69	5.81	-14.61
Kau Forest Reserve (Kapapala Sec.)	-20.51	-4.88	-12.23
Manuka Natural Area Reserve	-33.81	8.30	-11.06
South Kona Forest Reserve (Kapua-Manuka Sec.)	-17.35	-4.02	-10.90
Kipahoehoe Natural Area Reserve	-22.10	0.13	-9.88
Puu Waawaa Forest Bird Sanctuary	-12.62	-6.04	-9.85
South Kona Forest Res. (Olelomoana Opihihali Sec.)	-20.69	-0.91	-9.75
Kau Preserve (Nature Conservancy)	-28.72	3.25	-8.02

Table 6: Highlights of most severe anticipated precipitation decreases of protected areas (percentage in relation to baseline of each park)

Protected Area Name	**% Min**	**% Max**	**% Mean**
Hapuna Beach State Recreation Area	115.48	164.57	140.37
Kahoolawe Island Reserve	19.35	100.92	77.06
Hamakua Forest Reserve (Paauilo Sec.)	60.63	55.19	58.88
Kaiwi Scenic Shoreline	53.25	61.45	58.59
Diamond Head State Monument	53.45	49.71	51.95
Lapakahi State Historical Park	50.01	51.50	51.63

Hamakua Forest Reserve (Kalopa Sec.)	46.63	45.14	46.14
Kawainui Marsh Wildlife Sanctuary	47.45	39.79	44.71
Hamakua Forest Reserve (Hoea Kaao Sec.)	43.19	41.74	42.77
Hamakua Forest Reserve (Ahualoa Sec.)	38.37	43.27	40.06

Table 7: Highlights of most severe anticipated precipitation increases of protected areas (percentage in relation to baseline of each park) sorted by greatest percent increase in mean annual precipitation

Protected Area Name	**% Min**	**% Max**	**% Mean**
Mauna Kea Ice Age Natural Area Reserve	103.05	63.11	76.6
Alpine Wildlife Sanctuary	60.7	53.49	57.62
Mauna Loa Forest Reserve	84.89	41.70	53.69
Mauna Kea Forest Reserve	66.77	34.15	51.45
Keauhou Cooperative Nene Sanctuary	49.38	37.85	44.80
Kipuka Ainahou Nene Sanctuary	48.72	36.95	41.99
Kaonoulu Ranch Coop. Game Manage. Area	46.72	34.94	40.63
Kapapala Forest Reserve	74.66	32.58	40.10
Kula Forest Reserve	47.80	31.54	38.24
Nakula Natural Area Reserve	44.16	27.20	36.77

Table 8: Highlights of most severe anticipated temperature increases of protected areas (percentage in relation to baseline of each park).

Anticipated Future Native Vegetation Ranges based on Single-Category Random Forest Classification

Anticipated end of century potential distributions for Native Dry Forest, Native Dry Shrub, Native Mesic Forest, Native Mesic Grassland, Native Mesic Shrub, Native Wet Forest, and Native Wet Shrub were visualized using Forest-Based Classification and Regression with

NCAR RCP 8.5 temperature and precipitation inputs via the single category classification method in Figures 7-13. Across the entire archipelago, Native Dry Shrub is anticipated to experience the greatest contraction in range (Figure 8) followed by Native Wet Forest (Figure 12), while Native Mesic Forest is anticipated to experience the greatest expansion in range (Figure 9), followed by Native Mesic Shrub (Figure 11). Statistics on expansion and contraction in range for each vegetation type using Single Category Classification are described more thoroughly in Table 9. Protected areas experiencing the highest percentage and areas of vegetation loss and gain are summarized in Table 10.

Vegetation Type	**% NOT PRESENT**	**% LOSS**	**% GAIN**	**% NO CHANGE**
Native Dry Forest	80.63	8.83	5.73	4.81
Native Dry Shrub	60.42	13.59	18.20	7.79
Native Mesic Forest	60.84	8.86	18.89	11.42
Native Mesic Grassland	93.21	0.55	5.74	0.49
Native Mesic Shrub	66.78	8.55	15.89	8.79
Native Wet Forest	70.32	12.49	5.06	12.13
Native Wet Shrub	72.55	5.77	9.60	12.07

Table 9: Single Category Classification Future Statistics for each vegetation type

LOSS OF RANGE	**GAIN IN RANGE**
<u>**Native Dry Forest**</u> Mauna Kea FR / Wailiku silversword sanctuary (50%) Kipuka Anaihou Nene Sanctuary (49%) Puu Waawaa Forest Bird Sanctuary (48%) Kapapala Forest Reserve (47%) Kaonoulu Ranch Cooperative Game Management (46%) <u>**Native Dry Shrub**</u> Haena State park (87%) Keauhou cooperative Nene Sanctuary (81%) Mauna Kea FR / Wailuku Silversword sanctuary (75%)	<u>**Native Dry Forest**</u> Pohakuloa Training Area Reservation (100%) Kona Hema Preserve (44%) Mauna Loa Forest Reserve (34%) South Kona Forest Reserve (32%) West Maui Natural Area Reserve (28%) <u>**Native Dry Shrub**</u> Hamakua Forest (Multiple Sectors) (100%) Waihou Spring Forest Reserve (100%) Wailuku River State Park (100%) Manuka State Wayside (100%) Manowaialee Forest Reserve (96%)

Kanepuu preserve (71%) Pohakuloa training area Reservation (67%)	
Native Mesic Forest Keolonahihi State historical park (100%) Pohakuloa training area reservation (100%) Puu Waawaa Forest bird sanctuary (86%) Puu Alii natural area reserve (72%) Olokui Natural Area Reserve (64%)	**Native Mesic Forest** Keauohana Forest Reserve (100%) Lava Tree State Monument (100%) Polipoli Spring State Recreation Area (100%) Hamakua Forest Reserve (87%) Alpine Wildlife Sanctuary (80%)
Native Mesic Grassland Puu Alii Natural area reserve (81%) Olokui Natural area reserve (64%) Makawao Forest Reserve (29%) Hono o Na Pali Natural Area Reserve (22%) Keauhou Cooperative Nene Sanctuary (21%)	**Native Mesic Grassland** Upper Waiakea Bog Sanctuary (100%) Hakalau Forest National Wildlife Refuge (85%) Hilo Forest Reserve (81%) Ewa Forest Reserve (67%) Waikamoi Preserve (59%)
Native Mesic Shrub Upper Waiakea Bog Sanctuary (100%) Polipoli spring state recreation area (100%) Puu Waawaa Forest bird sanctuary (88%) Puu Alii Natural Area Reserve (56%) Kula Forest Reserve (53%)	**Native Mesic Shrub** Keauohana Forest Reserve (100%) Lava Tree State Monument (100%) Hamakua Forest Reserve (100%) Halekii-pihana Heiau state historic site (100%) Manuka State Wayside (100%)
Native Wet Forest Akaka Falls State Park (100%) Wao Kele O Puna (90%) Hilo Forest Reserve (Opea sec) (83%) Kau Forest Reserve (79%) Hamakua marsh wildlife sanctuary (66%)	**Native Wet Forest** Keolonahihi state historical park (100%) Waikamoi preserve (54%) Kipuka Ainahou Nene Sanctuary (53%) Hamakua Forest Reserve (Paaulio sec) (50%) Haleakala National Park (29%)
Native Wet Shrub Hilo Forest Reserve (Kaiwiki Sec) (57%) Akaka Falls State Park (50%) Kohala Forest Reserve (42%) Hilo Forest Reserve (41%) Nanawale Forest reserve (37%)	**Native Wet Shrub** Hamakua Forest reserve (85%) Alpine Wildlife Sanctuary (85%) Hamakua Forest Reserve (75%) Manowaialee Forest reserve (72%) Laupahoehoe Natural Area Reserve (71%)

Table 10: Top Five Most Extreme Gain and Loss by Vegetation Type, Protected Areas.

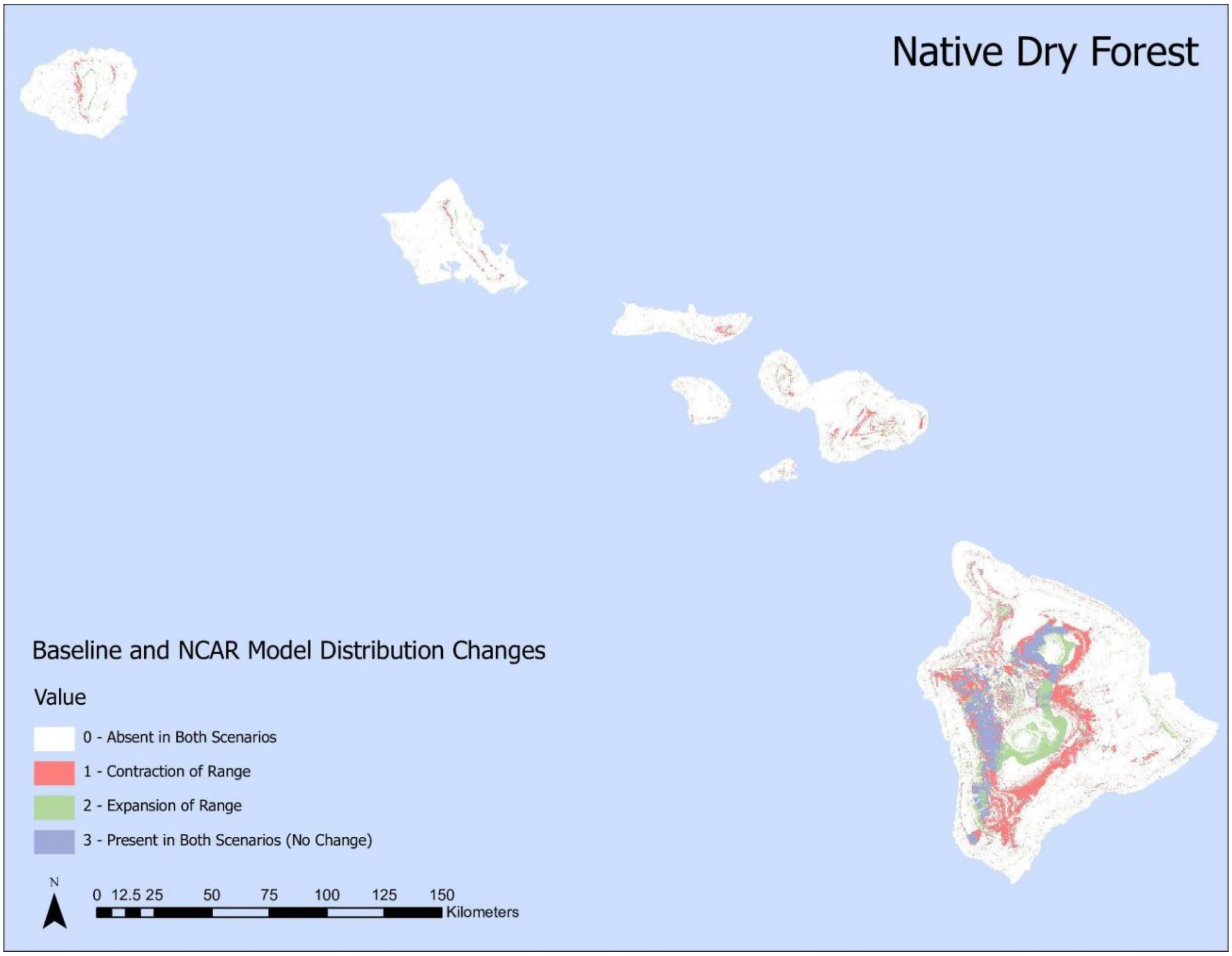

Figure 7: Future Native Dry Forest distributions (2090-2100) across the Hawaiian Islands using Forest-Based Classification and Regression with NCAR RCP 8.5 temperature and precipitation inputs.

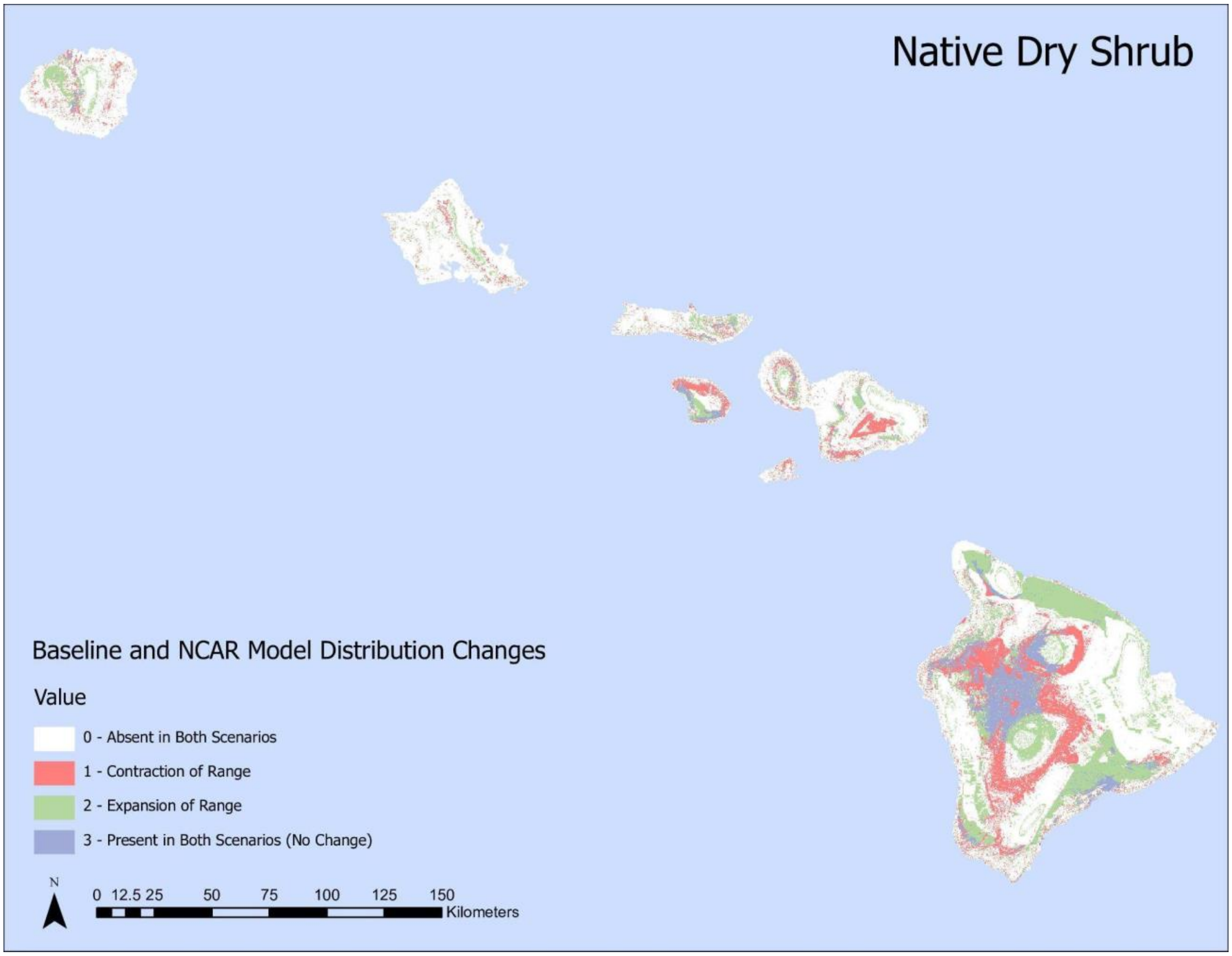

Figure 8: Future Native Dry Shrub distributions (2090-2100) across the Hawaiian Islands using Forest-Based Classification and Regression with NCAR RCP 8.5 temperature and precipitation inputs.

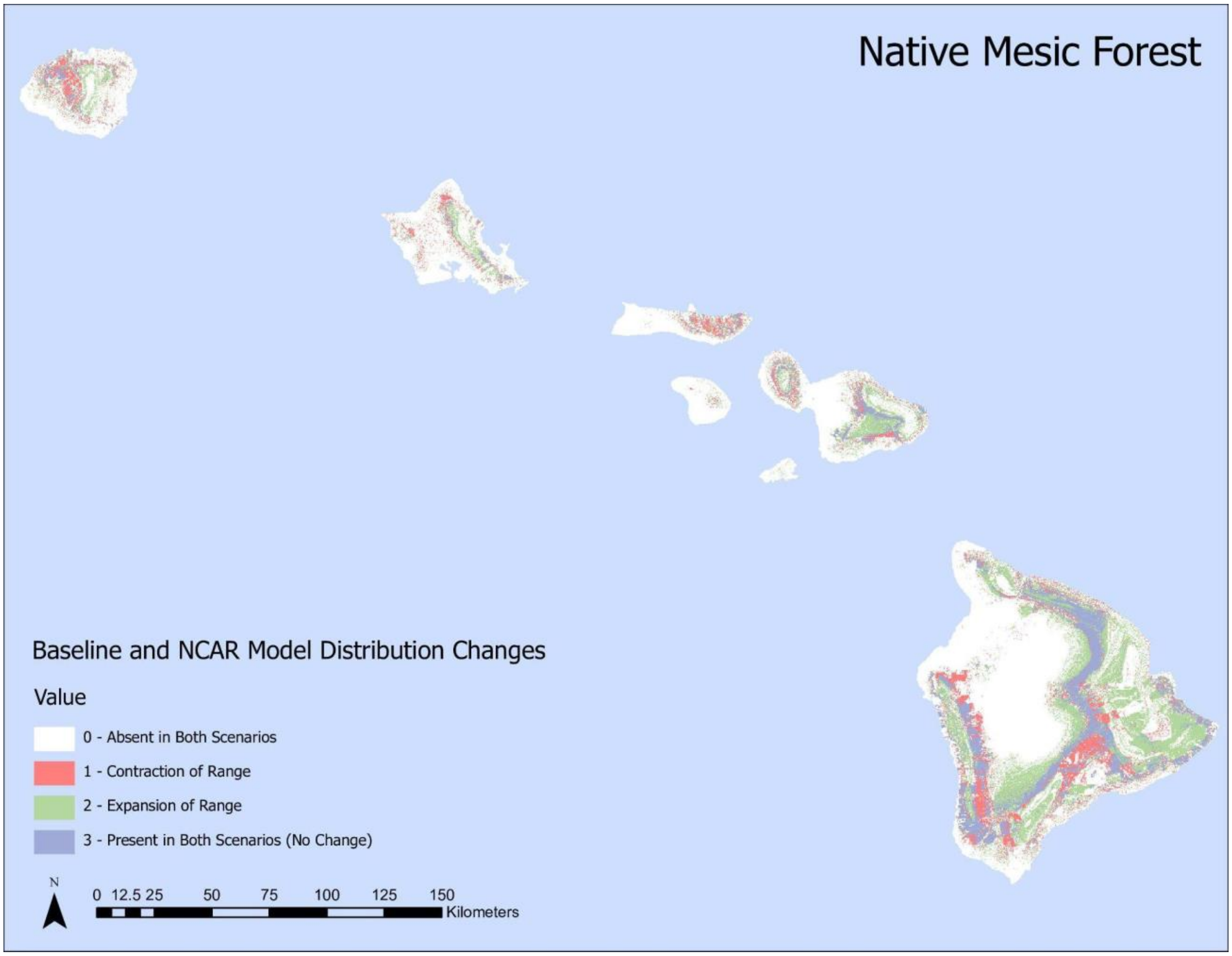

Figure 9: Future Native Mesic Forest distributions (2090-2100) across the Hawaiian Islands using Forest-Based Classification and Regression with NCAR RCP 8.5 temperature and precipitation inputs.

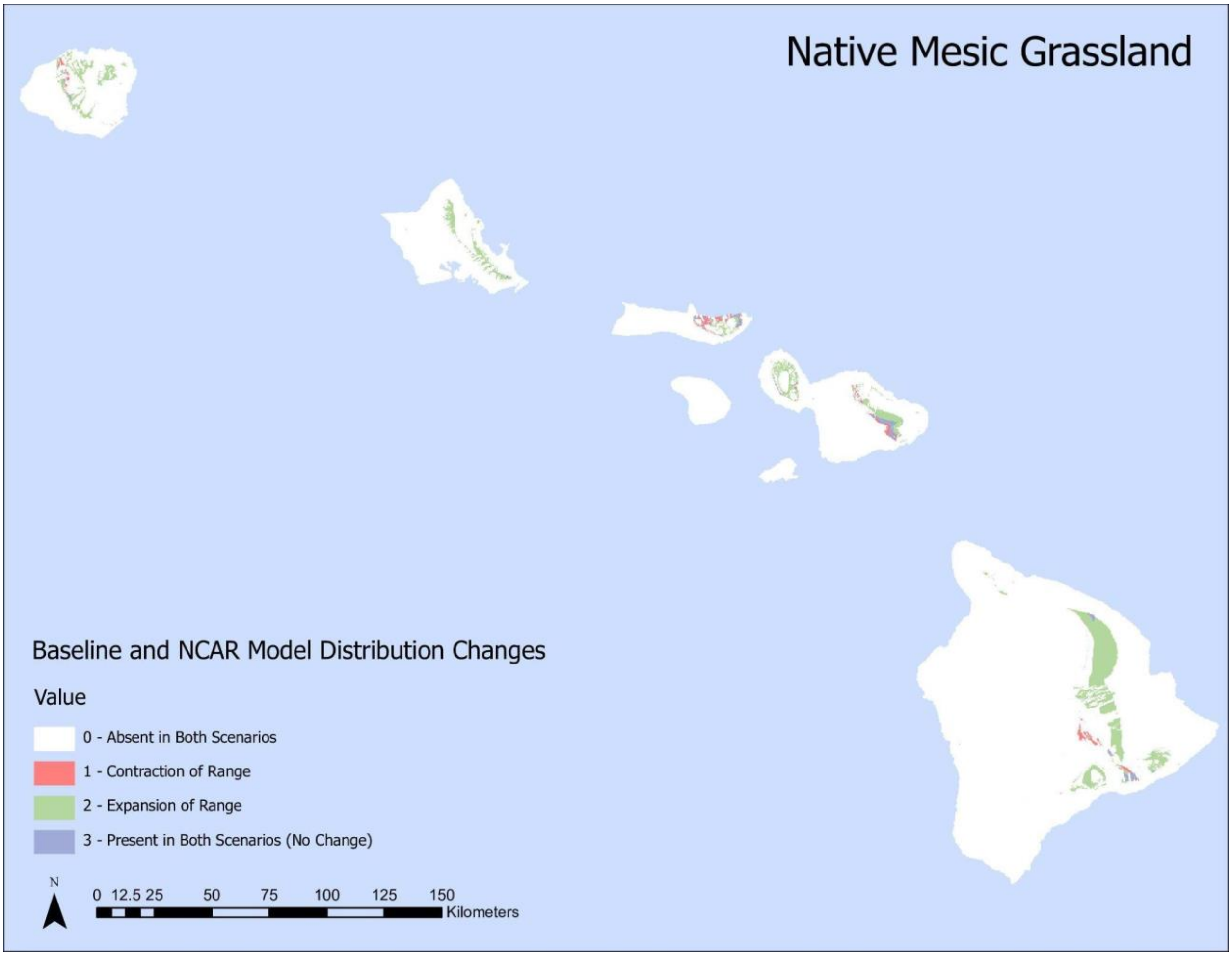

Figure 10: Future Native Mesic Grassland distributions (2090-2100) across the Hawaiian Islands using Forest-Based Classification and Regression with NCAR RCP 8.5 temperature and precipitation inputs.

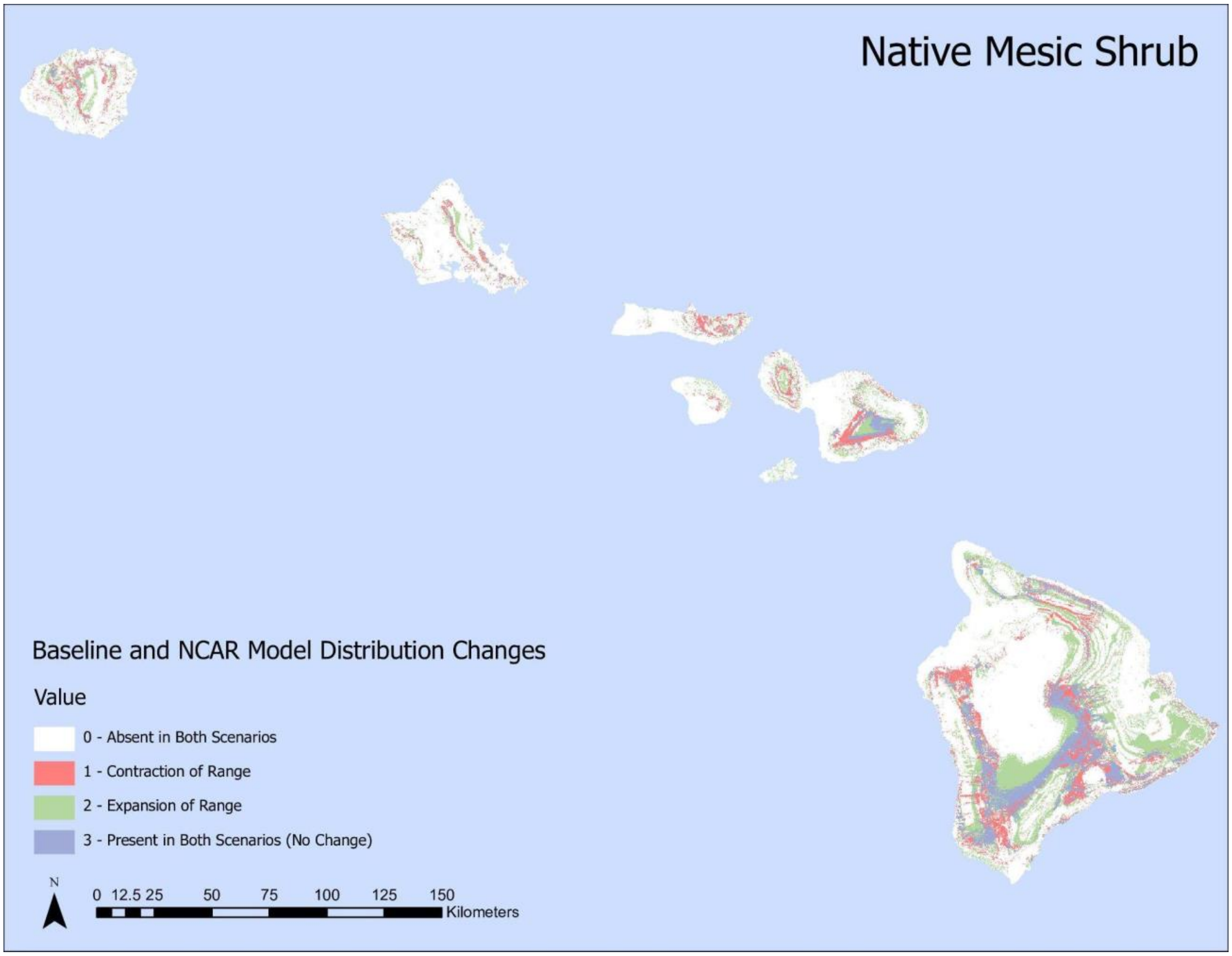

Figure 11: Future Native Mesic Shrub distributions (2090-2100) across the Hawaiian Islands using Forest-Based Classification and Regression with NCAR RCP 8.5 temperature and precipitation inputs.

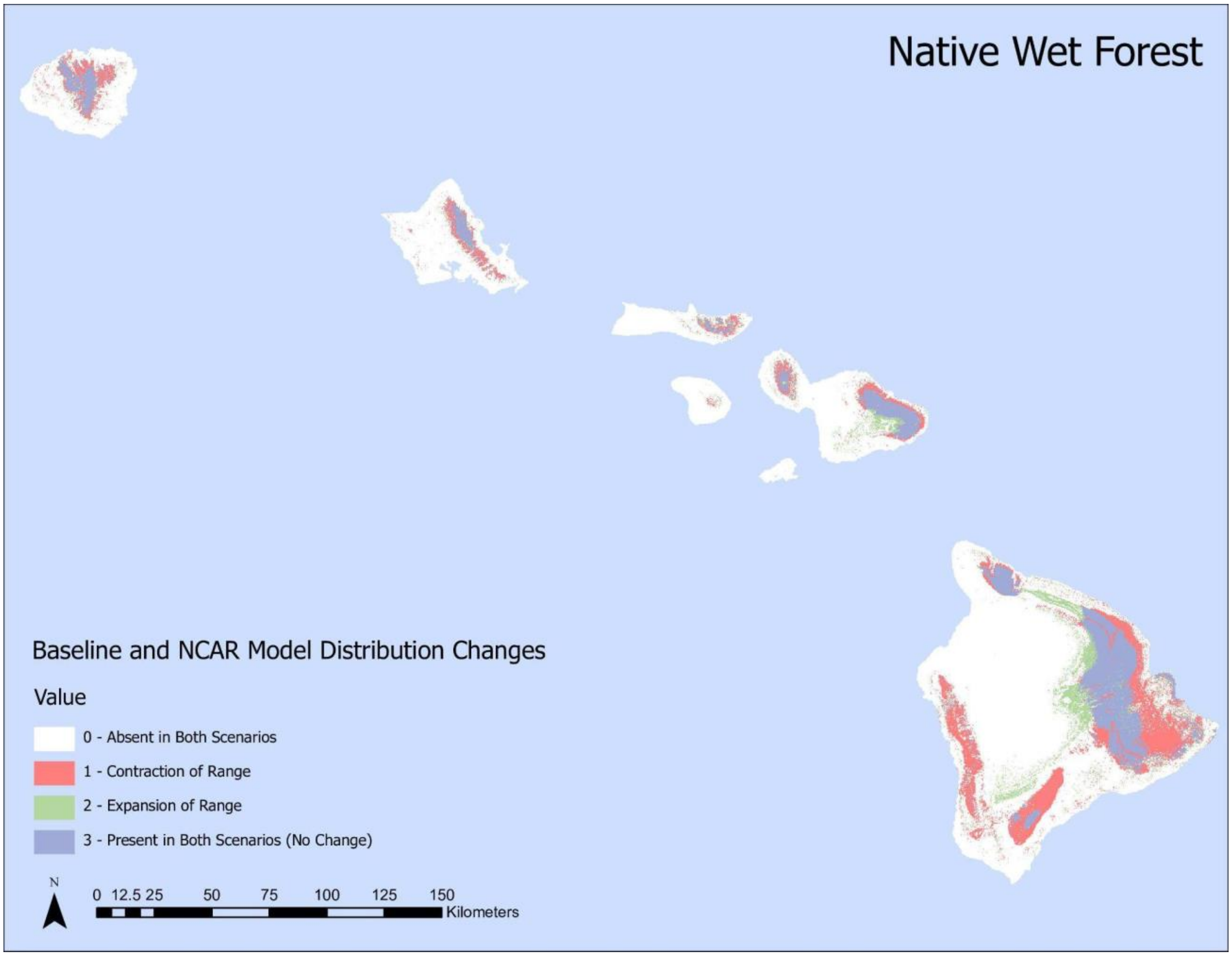

Figure 12: Future Native Wet Forest distributions (2090-2100) across the Hawaiian Islands using Forest-Based Classification and Regression with NCAR RCP 8.5 temperature and precipitation inputs.

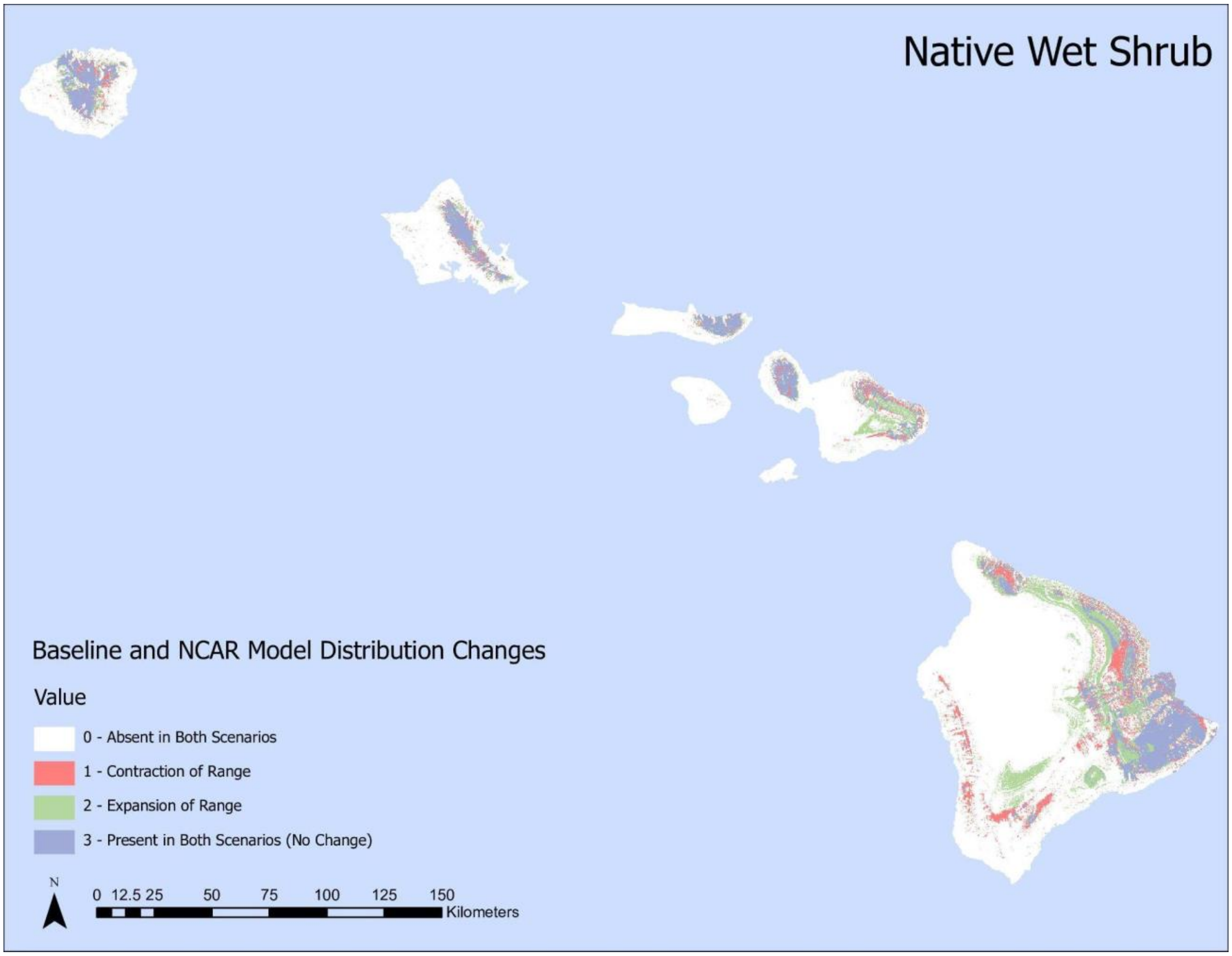

Figure 13: Future Native Wet Shrub distributions (2090-2100) across the Hawaiian Islands using Forest-Based Classification and Regression with NCAR RCP 8.5 temperature and precipitation inputs.

Single Class vs Multi Category Classification Approaches

Amongst all individualized Random Forest (Forest Based Classification and Regression) outputs utilizing baseline and NCAR RCP 8.5 predictions, accuracy remained above 82% for both training and validation data classification diagnostics. Variable importance varied, with soil order consistently ranking as the least important variable and other factors such as temperature and precipitation seasonality ranging from 20-30% in importance when assessing the model. The individualized, or Single Category Classification approach, resulted in multiple regions with anticipated overlap as seen in Figure 14. More specifically, 33.27% of the area has no overlap and predicts no suitability for any of the vegetation types while 12.75% of the area has a predicted future suitability for one vegetation type. When considering areas that do contain overlap, 20.70% of the area across the islands predicted future suitability for various combinations of two vegetation types, and 33.28% predicted future suitability for combinations of 3 or more vegetation types.

Alternatively, the multi-category approach for both baseline and future predictions resulted in an accuracy well above 97% in all categories except for “other”, which was at 91% accuracy for the baseline climate prediction and 93% accuracy for the future climate prediction. Variable importance for both baseline and future predictions ranked precipitation and temperature seasonality the highest, with all variables ranging from 19%-26% in importance and soil order ranking as the least important variable contributing less than 1% to the model. Table 8 highlights the change in land cover types between baseline and future scenarios using the multi-category classification model. Additionally, Figures 15 and 16 visualize these potential distribution ranges for each land cover class across the islands under baseline and future climate scenarios. In this case, the land cover type with the greatest expansion in range is predicted to affect Other/Unclassified non-native vegetation followed by Native Mesic Grassland and Native Dry Shrub, while the greatest contraction in range is anticipated to affect Native Dry Forest, followed by Native Wet Shrub and Native Wet Forest.

In the case of our study, the multi-category classification model had higher performance accuracy, yet it is important to note that multi-classification approaches may result in substantial bias due to the input of presence only data. The multi-category classification approach results in an exclusionary determination of vegetation type for each pixel, whereas the individualized approach allows for overlap and may be useful for highlighting regions that can sustain two or more vegetation types in the future.

Land Cover Type	**% Change**
Bare Ground	-5.38
Native Dry Forest	-57.35
Native Dry Shrub	+13.64
Native Mesic Forest	+12.21
Native Mesic Grassland	+44.74
Native Mesic Shrub	-9.43
Native Wet Forest	-46.18
Native Wet Shrub	-50.33
Other Non-Native Vegetation	+53.06

Table 8: Multi Category Classification Future Statistics for each vegetation type.

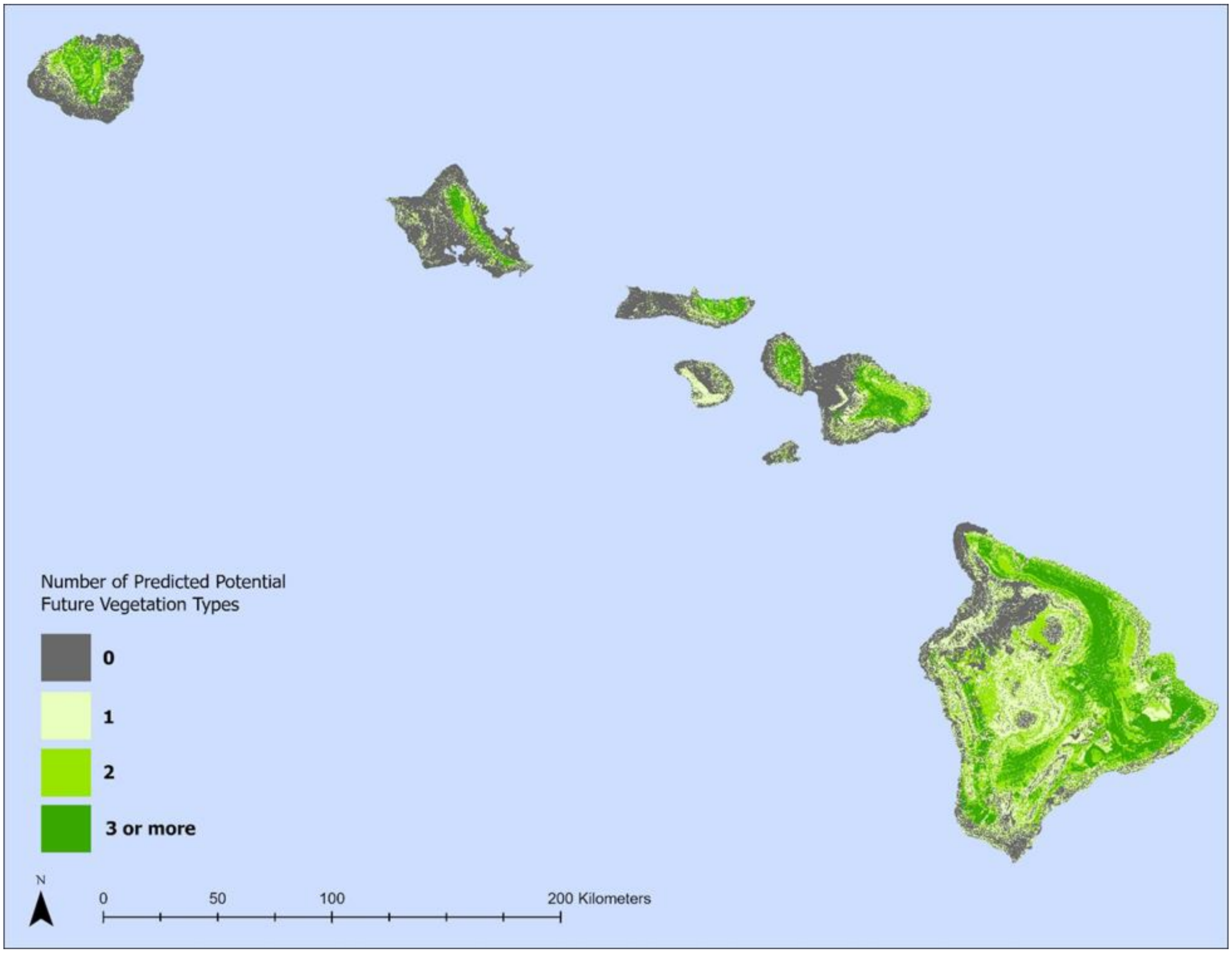

Figure 14: Number of predicted potential future vegetation types and distributions across the Hawaiian Islands (2100 estimate) by assessing product overlap using the Single-Category classification method.

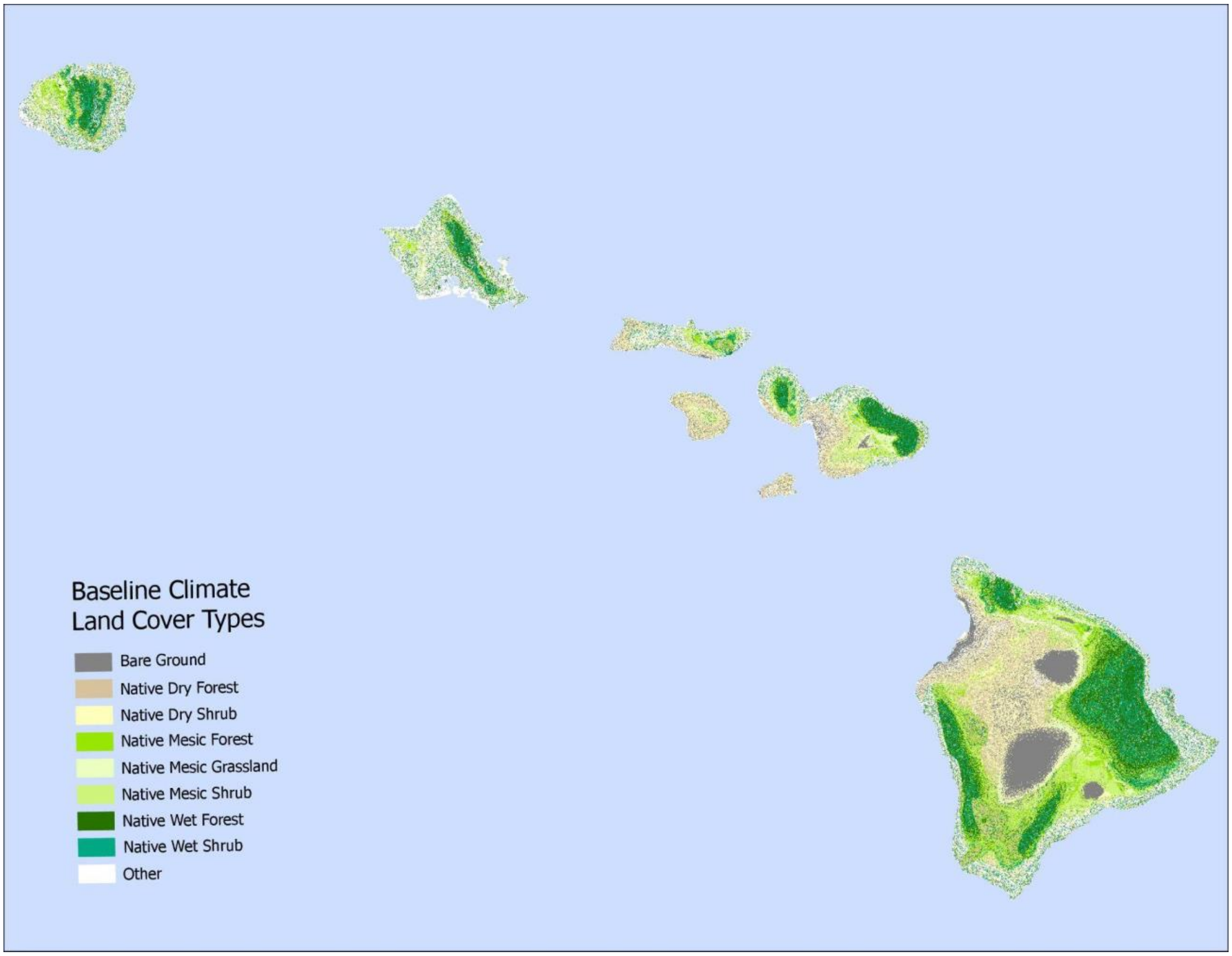

Figure 15: Baseline (Current) Potential Land Cover distributions using Forest-Based and Boosted Classification multi category approach.

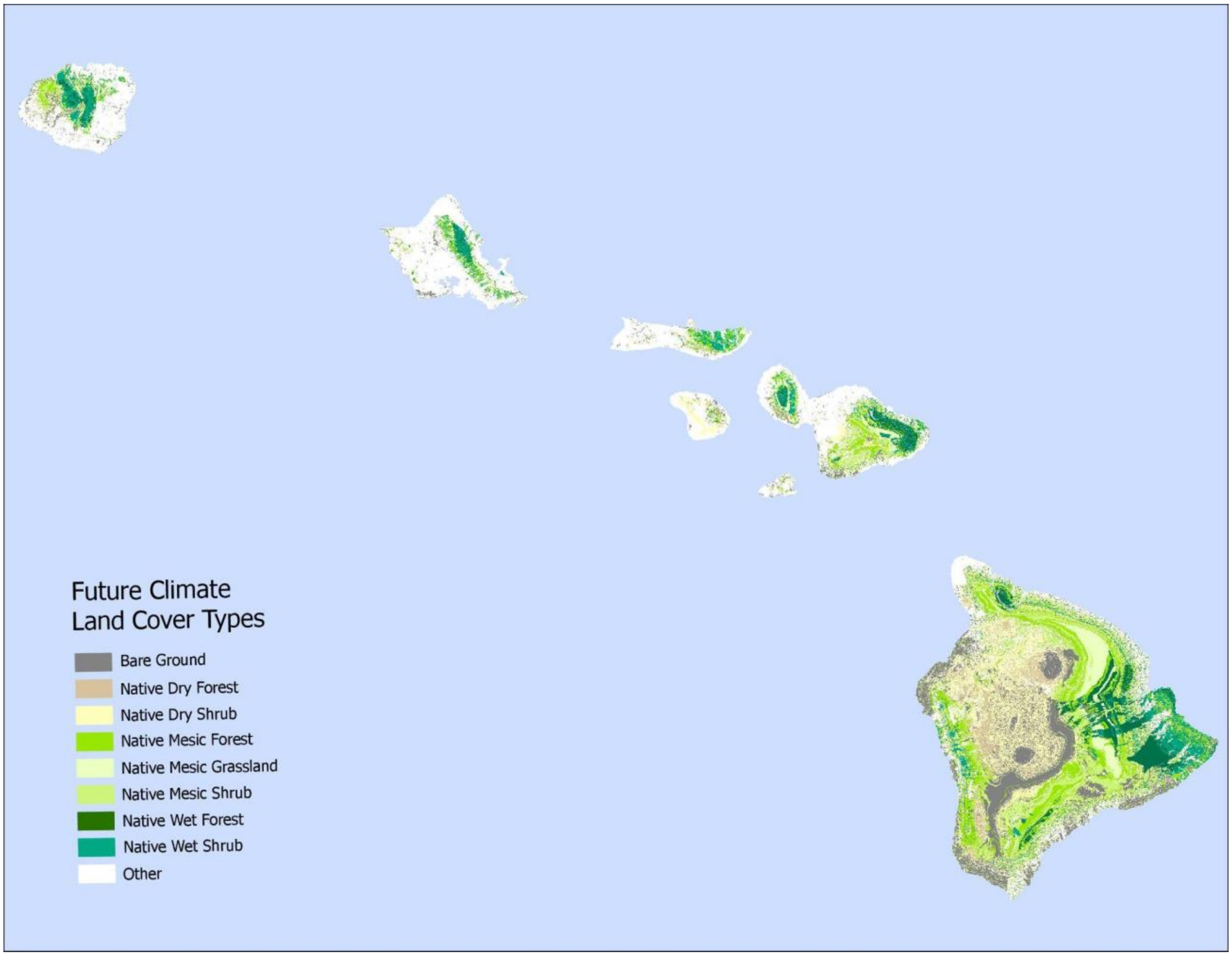

Figure 16: Future (2100) Potential Land Cover distributions using Forest-Based and Boosted Classification (ArcGIS Pro 3.2) multi-category approach.

Discussion

Confinements of Scale

The scale and resolution of data play a critical role in shaping scientific and geographic analyses, especially when assessing the effects of climate change. In regions like the Hawaiian Islands, which is characterized by diverse topography and microclimates, the resolution of climate data affects how accurately localized variations, such as rainfall patterns or temperature changes in coastal versus mountainous areas, are captured (PIRCA, 2012). Coarse-scale data may obscure these local differences, while higher-resolution data, though more resource-intensive, can provide finer details necessary for understanding climate impacts on ecosystems (Fortini et al. 2022). Moreover, temporal resolution influences how well short-term fluctuations can be distinguished from long-term climate trends, which is crucial for accurate climate predictions and adaptation planning. The limits of data resolution also pose challenges in understanding the full scope of climate change. High-resolution models allow for a more precise simulation of local climate dynamics, such as sea-level rise or extreme weather events, but their computational demands make them less feasible for large-scale applications (Fortini et al. 2022). On the other hand, coarse-scale models might not fully capture critical small-scale processes or the vulnerability of ecosystems, particularly in places like Hawaii, where endemic species and communities are highly sensitive to climate fluctuations (Eversole 2014). Thus, balancing data resolution with computational limitations is essential to accurately assess climate risks and inform effective policy and conservation strategies.

Climatic Niche of Remaining Native Vegetation

To assess the impacts of climate change on vegetation types it is critical to understand if vegetation types have distinct climate niches. This is commonly done for individual native species on individual islands (Rovzar et al. 2016) and across the Hawaiian Islands (Fortini et al. 2022). However, examining native vegetation types based on high resolution vegetation types is less common in the Hawaiian Islands and other islands in the Pacific. Using randomized points within seven native vegetation types from the Carbon Assessment of Hawaii Land Cover Map from Jacobi et al. (2017) we show that there are significant differences in temperature and precipitation among and between native vegetation types. This suggests that although many vegetation types have been deforested and fragmented (e.g. native dry forest) they still maintain unique climate niches on the Hawaiian Islands. Indeed, the lowest similarity in climate metrics was between native mesic grasslands and native dry forest (Figure 6) and globally it is well known that these vegetation types can exist in the same climatic niche and are heavily influenced by other factors such as fire and soil moisture (Murphy and Bowman 2012, Ocón et al. 2021). Otherwise, all one-on-one comparisons between native vegetation types had different climate niches. Understanding native vegetation distributions and dynamics on tropical islands or continents is critical for any study of climate and vegetation change and results suggest that high resolution vegetation maps and randomized point locations can be used to test this hypothesis in the Hawaiian Islands and other regions.

Predicted Climate Change in Protected Areas

We examined baseline and downscaled future climate projection using the NCAR RCP 8.5 projection to estimate the changes of the individual bioclimatic variables compared to the baseline scenario to determine the direction and amount of change anticipated for protected areas within our study area (Fortini et al. 2022). We selected this model because we felt the national NCAR models provide the most detail on methods and effectivity compared to other climate projections (Neale et al. 2010) and we wanted to experiment with single category vs multi-category vegetation models using a single climate model as our environmental input. Results based on the NCAR RCP 8.5 projection show significant changes in both the absolute value and percentage change of temperature and precipitation metrics within protected areas of the Hawaiian Islands.

However, it is important to recognize the variability that exists between different climate models. Fortini et al. (2023) explored rainfall projections from globally downscaled datasets such as CHELSA and WorldClim2, revealing significant variability in their predictions, especially when compared to regional models. For the case study of Hawaiʻi, the study identified that these global datasets often misrepresent localized precipitation patterns, either overestimating or underestimating projected changes. For example, while one dataset might indicate a pronounced drying trend in certain regions, another might predict stable or even increasing rainfall, leading to inconsistencies. In the case of our NCAR data, the end of century projections have higher annual estimated precipitation on average compared to other existing models (Fortini et al. 2023). These discrepancies arise partly due to differences in baseline datasets used by global and regional models, which significantly influence the magnitude and spatial patterns of projected precipitation. Such variations have profound implications for applications reliant on accurate precipitation data, such as hydrological modeling or ecosystem impact assessments. Therefore, unchecked use of these projections could propagate inaccuracies into downstream analyses. For instance, species distribution models derived from biased precipitation data might inaccurately forecast habitat shifts, with potentially significant ecological consequences.

Protected area impacts can be assessed through both absolute change in temperature and precipitation (Table 3) as well as percent change in relation to the area's baseline (Tables 6, 7, and 8). With regards to absolute temperature change particularly in areas anticipated to have a mean rise in temperature of 4.5 °C or higher, Mauna Kea Ice Age Natural Reserve, Hawaii Volcanoes National Park, Kapapala Forest Reserve, Mauna Kea Forest Reserve, and Mauna Loa Forest Reserve have the highest anticipated change in maximum temperature. However, Mauna Kea Ice Age Natural Area Reserve, Alpine Wildlife Sanctuary, Mauna Loa Forest Reserve, Mauna Kea Forest Reserve, Keauhou Cooperative Nene Sanctuary, Kipuka Ainahou Nene Sanctuary, Kaonoulu Ranch Cooperative Game Management Area, and Kapapala Forest Reserve are all projected to have a mean annual temperature increase of more than 40% by the end of the century, meaning that these areas are susceptible to the greatest level of heat related risk. It is also important to note that these high-risk areas susceptible to temperature increases are found on multiple islands including Hawaii, Kauai, Oahu, and Maui.

Protected areas are also anticipated to endure a significant amount of change in precipitation. With regards to the greatest annual decrease in rainfall, Kona Hema Preserve (Nature Conservancy), Kapapala Forest Reserve, Kau Forest Reserve, Kau Forest Reserve (Kapapala Sec.), Manuka Natural Area Reserve and South Kona Forest Reserve (Kapua-Manuka Sec.) are all anticipated to experience a decrease in mean annual precipitation by 10% or more, with some regions expected to have more than 20% change in mean annual precipitation and even more drastic changes in minimum and maximum predicted change in annual precipitation.

However, not all regions across the islands are equally affected. For instance, Wailua River State Park, Kaloko-Honokohau National Historical Park, Kawainui Marsh Wildlife Sanctuary, James Campbell National Wildlife Refuge, and Kaiwi Scenic Shoreline are anticipated to have some of the least severe temperature increases according to the NCAR Climate model, however these regions are still tentatively projected to increase by 3 °C as we approach the end of the century. With regards to precipitation, areas such as Waiakea 1942 Lava Flow Natural Area Reserve, Kuaokala Forest Reserve, Waiaha Springs Forest Reserve, Puu Honau O Honaunau National Historical Park and Olaa Forest Reserve (Mt. View Sec.) are expected to have little to no change in precipitation trends.

It should also be noted that while this study utilized the NCAR climate projections for bioclimatic variables across the Hawaiian Islands (Fortini et al. 2022) the same data source also features access to two other downscaled climate models from the International Pacific Research Center, with results on changes in temperature and precipitation are dramatically different than our NCAR model. Our study aims to utilize the NCAR model as a potential scenario because it is a validated and realistic input (Xue et al. 2020) that utilizes historical simulations to effectively reproduce the mean surface temperature, relative humidity, and winds in the model with exceedingly low biases and high spatial correlations. However, the methodology described in this paper can be used through various climate models if they provide adequate variables that can be used to determine potential species ranges under future climates. Indeed, future climate models will continue to improve and provide more accurate climate change predictions over time, however, there is currently an immense gap in knowledge regarding the proper methodology to study the potential impact of climate change on native vegetation in areas with high quantities of threatened endemic species. This knowledge is particularly crucial for natural resource managers and government officials who rely on a combination of climate models, species distribution metrics, and various validation methods to justify these findings and test predicted climate and vegetation results under machine learning algorithms. A simple way to address the variation in end of century climate models would be to ensemble all of the existing IPCC climate models and downscale final model results (Mizukami et al. 2022).However, given the uncertainty that comes with an analysis of this scale, our recommended future direction is to validate each model individually over time and use the single model that coincides with the validation results.

There are several satellite sensors that measure land surface temperature and precipitation at moderate resolutions that can be used to validate climate change models from 2000 to present. NOAA (VIIRS) and EOS (MODIS) provide land surface temperature (LST) products at 1 km spatial resolution while remote sensing data on precipitation at 0.1 degree (10 km) from NOAA satellites and from the Global Precipitation Measurement Mission is also available. Thus, a near 25-year time series at 1 km for temperature and 10 km for precipitation is available to test if predicted change or trajectories are occurring within protected areas.

Single Class vs Multi Category Classification Approaches

This research shows that it is possible to incorporate fine scale baseline and future climate projections into a Forest-Based Classification and Regression Model using two different approaches to determine potential impacts and changes in distributions for native vegetation types by the end of the century in response to climate change. Climate Change Vulnerability Assessments (VAs) have been conducted in various regions across the world (Foden et al. 2019, Comer et al. 2019) however there has been limited research conducted on the Hawaiian Islands due to the complexity of the landscape and the need for very high-resolution climate data that covers the region. Furthermore, there has been limited knowledge on vegetation responses to climate change in regions defined as protected areas on the Hawaiian Islands. This study is the first of its kind to incorporate recent and validated land cover maps from the Carbon Assessment of Hawaii (Jacobi et al. 2017) into a machine learning algorithm to group and classify native vegetation distributions and create fine scale range maps with a detailed assessment on protected area climate impacts for future projections going into 2100. This research provides a framework for modeling climate change impacts on the distribution of endangered native species on small, remote Pacific islands, and may be used to conduct vegetation vulnerability assessments on other remote regions experiencing similar threats. Evaluating the changes in native vegetation distribution and range that may result from climate change allows for reserves to coordinate relocation efforts, provide supplemental resources for high-risk regions, and take the necessary measures to protect endangered species from extinction.

When applying this model to practical efforts it is important to note that we are not predicting migrations of native vegetation classes themselves under future climates; rather, we are predicting differences in spatial patterning of the climatic conditions where current native vegetation assemblages may exist under future climates. Furthermore, the results of this model should not be used as an absolute identification of native vegetation range on the islands but should serve as an indicator for potential suitable habitats that may require additional factors for validation. 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 native vegetation categories. Both the individualized distribution ranges and the multi-category classification assessment provide valuable insight regarding ecosystem dynamics and climate change related impacts on these isolated islands. While the multi-category classification model has a much higher performance accuracy, it is important to consider that multi-classification approaches may result in substantial bias due to the input of presence only data (Elith et al. 2006). Additionally, the multi-category classification approach results in an exclusionary determination of vegetation type for each pixel, whereas the individualized approach allows for overlap and may be useful for highlighting regions that can sustain two or more vegetation types. Further refinement may be necessary for this model to improve accuracy by incorporating additional environmental variables such as slope, aspect, evapotranspiration, and other factors. Lastly, incorporating different future climate scenarios and providing alternative distribution models based on the described methods may better inform land management decisions and prepare high risk protected areas in Hawaii.

Limitations

While our study is the first of its kind to provide results on potential native vegetation ranges utilizing forest-based classification from baseline and future climate projections, there are limitations to consider. It is important to note that while there has been extremely limited research on the topic, one study found evidence of anticipated mesic forest contraction and dry shrubland expansion that directly contradicts our projected expansion of dry shrubland and other low-moisture vegetation types into current areas containing wet forest (Fortini et al. 2018). This contradiction may be a result of differences in vegetation groupings, baseline and future climate data inputs, and the separation of native and non-native vegetation types between studies. However, both studies provide valuable input by providing multiple perspectives for land use and conservation efforts, especially for areas that show agreement between the two studies (Fortini et al. 2018). There have been a number of studies that show how climate change is impacting vegetation migrations along elevational (Koide et al. 2017) and latitudinal gradients (Holsinger et al. 2018). However, it is currently extremely difficult to validate vegetation change under future climate scenarios, and when we consider validation methods for this study we must remember that we are not predicting migrations of vegetation classes themselves under future climates, but rather we are predicting differences in spatial patterning of the climatic conditions where current native vegetation assemblages may exist under future climates. While most studies of this variety examine changes in vegetation using NDVI increases to validate expansion and contraction, this approach cannot be applied to our study because changes in NDVI cannot clearly indicate the presence of one species over another, and our study does not account for factors that affect seed dispersal and migration. Currently the most efficient way to validate this study is through the observation of field sites and weather monitoring systems, which can effectively validate the results by demonstrating similarities and determining the accuracy of the climate model and spatial patterning of suitable climate conditions. It is important to consider that future temperature and precipitation patterns play a significant role in determining potential suitable ranges for the native vegetation in our study, meaning that the lack of climate model variations is another major limitation in our research. Our study utilized one predicted climate scenario, NCAR RCP 8.5, however there is wide variation in existing downscaled models for the region as well as the existing IPRC models within our bioclimatic variable dataset. Additionally, our study utilized mean annual temperature, mean annual precipitation, precipitation seasonality (Coefficient of variation for monthly precipitation), and temperature seasonality (standard deviation * 100) as our climatic variable inputs, however it is important to note that rage of variability and other characteristics of climate may play an additional role in affecting vegetation within the region. Our model functions under the simple assumption that the only way climate influences vegetation distributions and future potential ranges is through changes in temperature and precipitation, therefore those were the only variables that were changed between the baseline and future scenarios in our machine learning algorithms.

There is also the issue of determining the most effective method for assessing anticipated vegetation ranges using machine learning. One of our main limitations is our inability to fully validate our results of anticipated vegetation expansion, contraction, and areas not anticipated to change. For instance, our study had two different methods for determining potential future vegetation ranges, which resulted in moderate variability and differences between the two outputs. One primary advantage of the single-category classification approach is the ability to clearly illustrate potential zones of expansion and contraction for each vegetation type, which can then also be used to map areas of overlapping future climate suitably for each of the vegetation categories. On the other hand, the multi-category classification approach simplifies this process by determining the most likely vegetation type given the input baseline climate data and future climate scenario. While this method creates a clear output that can be used to calculate anticipated vegetation distribution ranges for all species, it does not allow the user to clearly assess individual expansion and contraction of range for a given land cover category. Furthermore, while this method may be the simplest method for land management and conservation planning, it does not clearly highlight areas that may have overlapping suitable conditions, which could be a critical factor when relocating species found in high-risk regions.

We must also consider other factors beyond climatic conditions that may impact end of century vegetation ranges. One of the most disruptive and unpredictable factors to consider is fire. While certain types of vegetation and drought conditions are more prone to wildfire, the extent and severity of fire events is impossible to accurately predict. Fire is known to drastically impact composition and structure of native vegetation types as seen in the case of Hawaii Volcanoes National Park (Ainsworth and Kauffman 2013) where repeated fires resulted in lower tree survival and rapid occupation by aggressive herbaceous species. Another critical concern is invasive species, which have a multitude of impacts on plant communities through their direct and indirect effects on soil chemistry and ecosystem function. For instance, there is evidence that invasive plant species may alter nutrient cycles differently from native species by modifying the soil environment through root exudates, thus permanently changing the local soil structure and making it increasingly difficult for native plants to adapt and survive (Weidenhamer and Callaway 2010). While these concerns cannot be accurately predicted using machine learning technology at the moment, it is important to rely on a combination of climate-based future vegetation analysis and expert opinions from those who can relay critical local and/or indigenous knowledge when considering fire, invasive species, and pest/disease impacts in the context of land management and species conservation across the Hawaiian Islands.

Case Study: Hawaii Volcanoes National Park and Haleakala National Park

It is critical to assess habitats on both grand and small scales to better prepare specific high-risk regions for anticipated climate impacts. In the case of Hawaii Volcanoes National Park, about 80% of the total protected area is now composed of fire derived, degraded grasslands dominated by non-native species, or sparsely to unvegetated volcanic terrain (Loope et al. 2013) while the remaining area of about 250–300 km^2 contains vast amounts of diverse native plant communities. Both Hawaii Volcanoes National Park and Haleakala National Park are projected to experience record breaking peaks in temperature by the end of the century while enduring significant decreases in annual precipitation. Therefore, the multi-category approach for Forest Based Classification and Regression in ArcGIS Pro was used to quantify potential changes in distributions by the end of the century for these protected areas. Current distributions for Hawaii Volcanoes National Park are 30% bare ground, 5% Native Dry Forest, 6% Native Dry Shrub, 13% Native Mesic Forest, 7% Native Mesic Grassland, 20% Native Mesic Shrub, 4% Native Wet Forest, 6% Native Wet Shrub, and 9% for other vegetation types. Bare ground and Native Dry Shrub are expected to have the greatest expansion of range by 2100, increasing by 7% and 12% respectively. Alternatively, Native Mesic Grassland, Native Wet Forest, and Native Wet

Shrub are anticipated to experience the most severe contraction in range, decreasing by 4%, 3%, and 5%. Haleakala National Park's baseline distributions are 8% Bare Ground, 2% Native Dry Forest, 6% Native Dry Shrub, 8% Native Mesic Forest, 26% Native Mesic Grassland, 16% Native Mesic Shrub, 15% Native Wet Forest, 11% Native Wet Shrub, and 8% for other land cover types. Native Dry Shrub and Native Mesic Forest are anticipated to expand by 4% and 12% respectively, while Native Mesic Grassland and Native Wet Forest are anticipated to decrease by 11% and 4% in range. Figures 17 and 18 highlight these new potential vegetation distribution ranges for these regions by the end of the century.

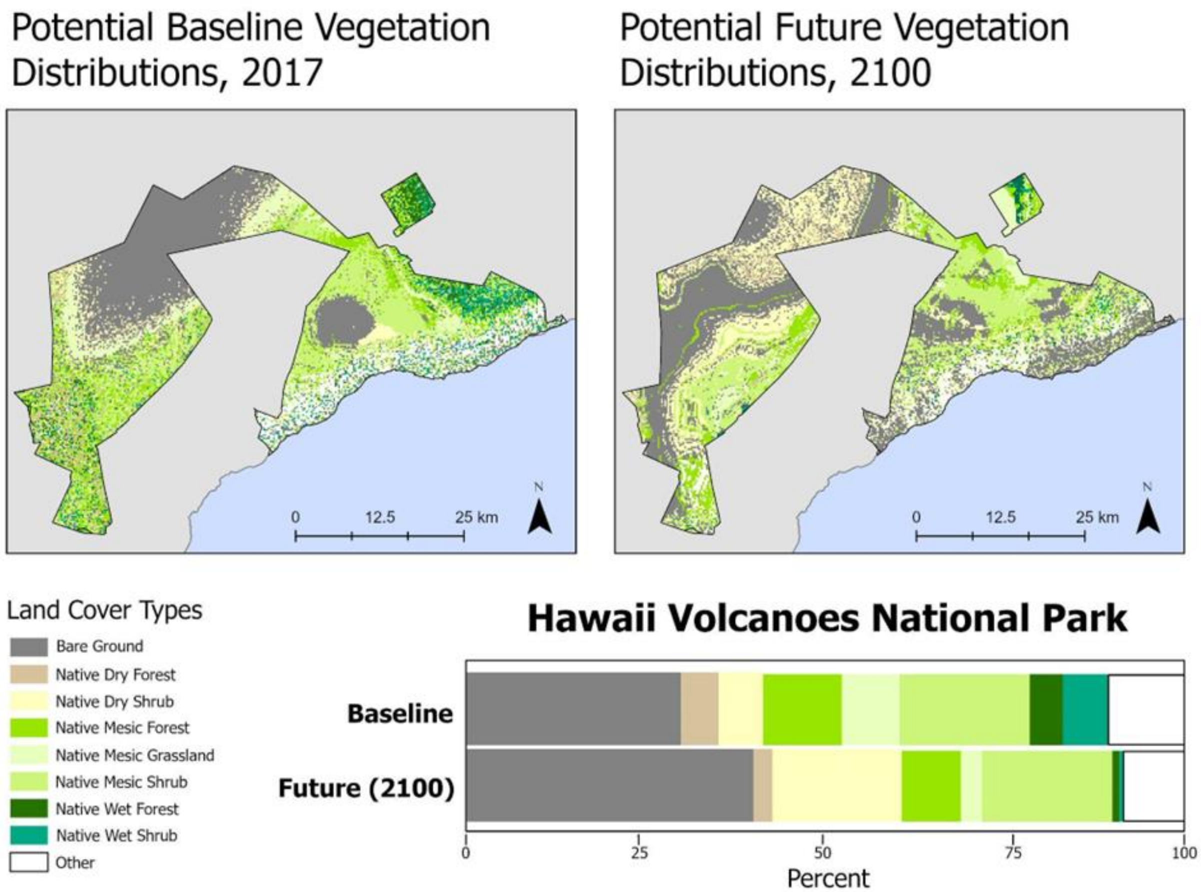

Figure 17: Projected potential vegetation distributions for Hawaii Volcanoes National Park featuring baseline and future (2100) scenarios using NCAR RCP 8.5 climate projections as an input for the Forest Based and Boosted classification and regression tool (ArcGIS 3.2) through the multi-category classification approach.

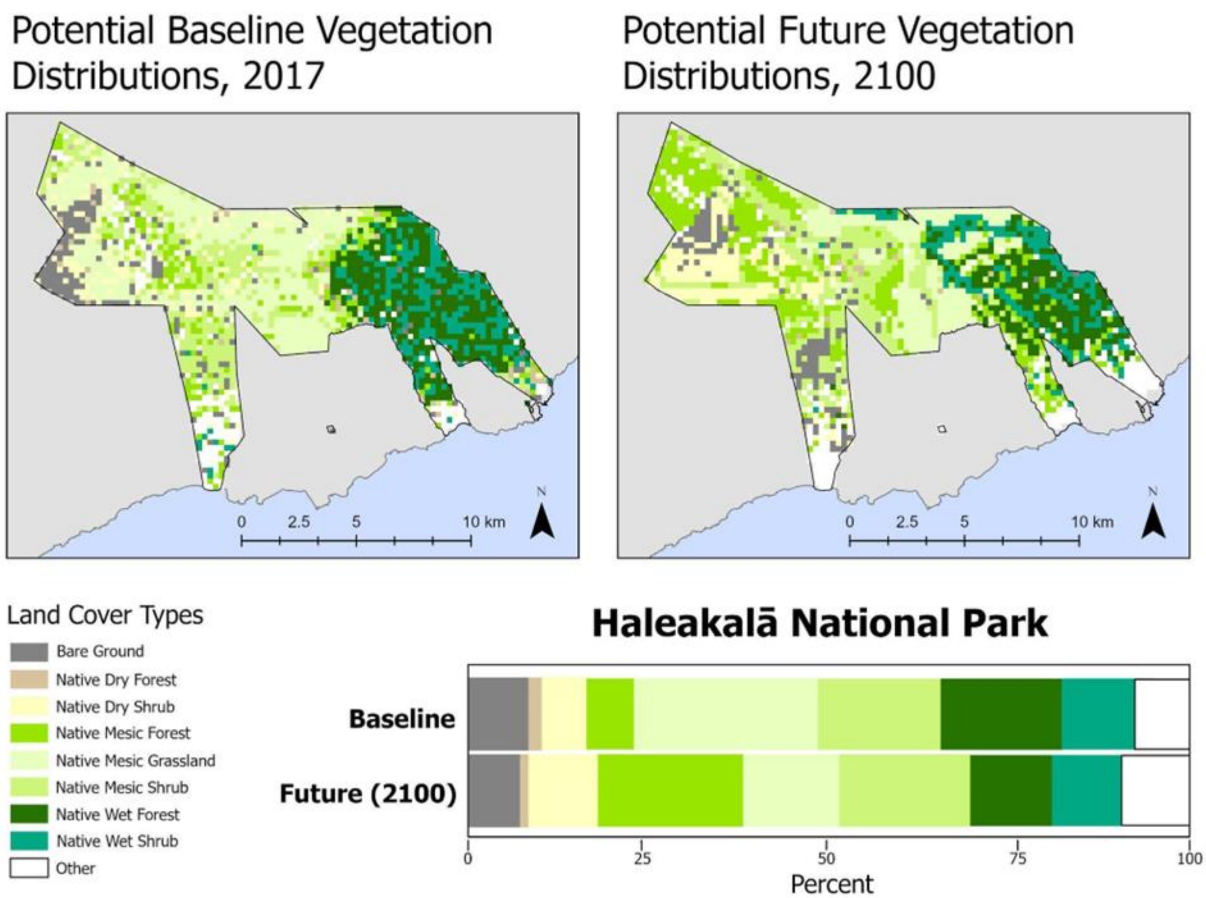

Figure 18: Projected potential vegetation distributions for Haleakala National Park featuring baseline and future (2100) scenarios using NCAR RCP 8.5 climate projections as an input for the Forest Based and Boosted classification and regression tool (ArcGIS 3.2) through the multi-category classification approach.

In addition, we determined the areas of overlapping potential suitability for all seven native vegetation types using the Single-Category classification method for both national parks to further assess discrepancies and accuracy between the two classification methods. Figures 19 and 20 depict these predicted potential future vegetation types and distributions for 2100.

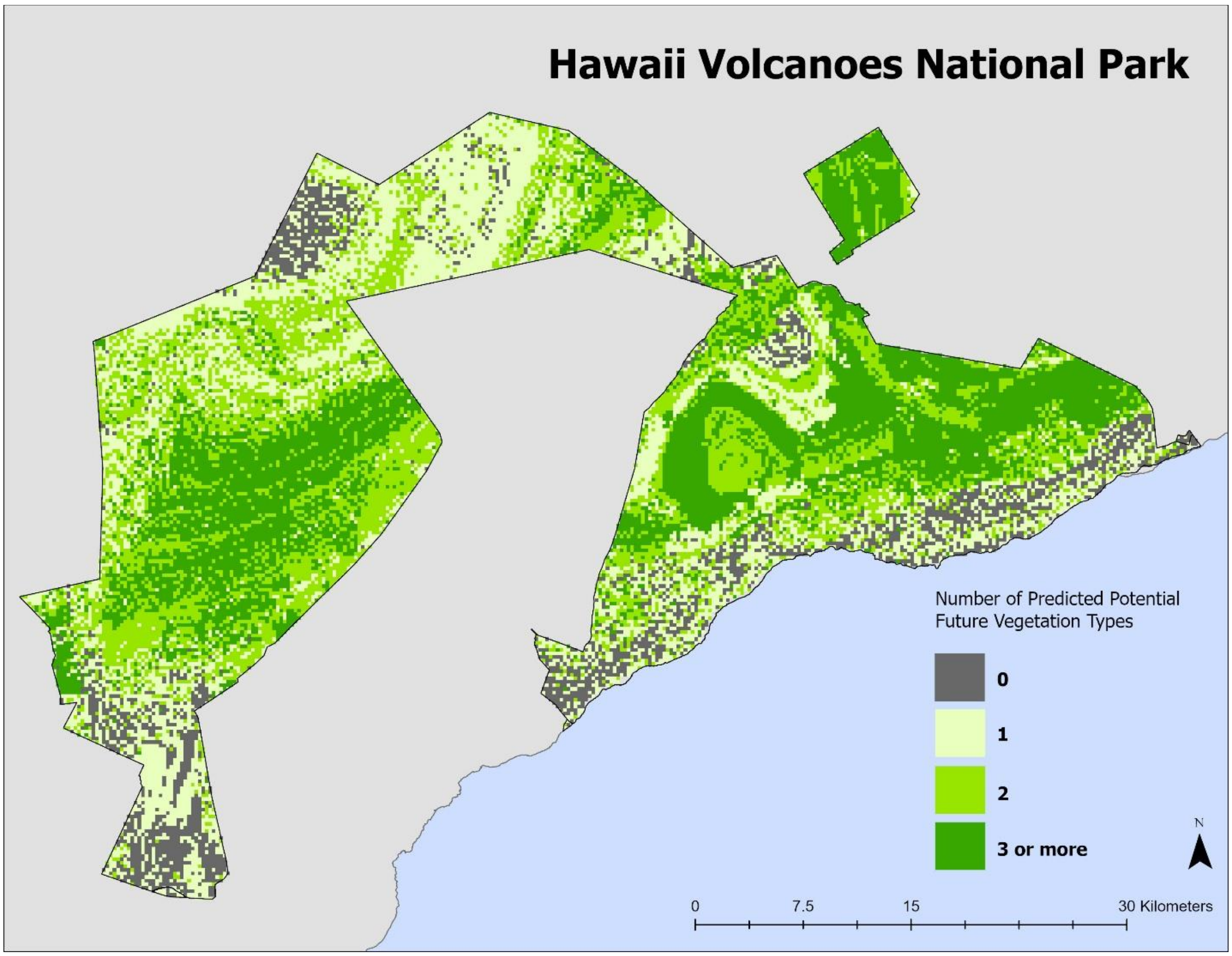

Figure 19: Number of predicted potential future vegetation types and distributions in Hawaii Volcanoes National Park (2100 estimate) by assessing product overlap using the Single-Category classification method.

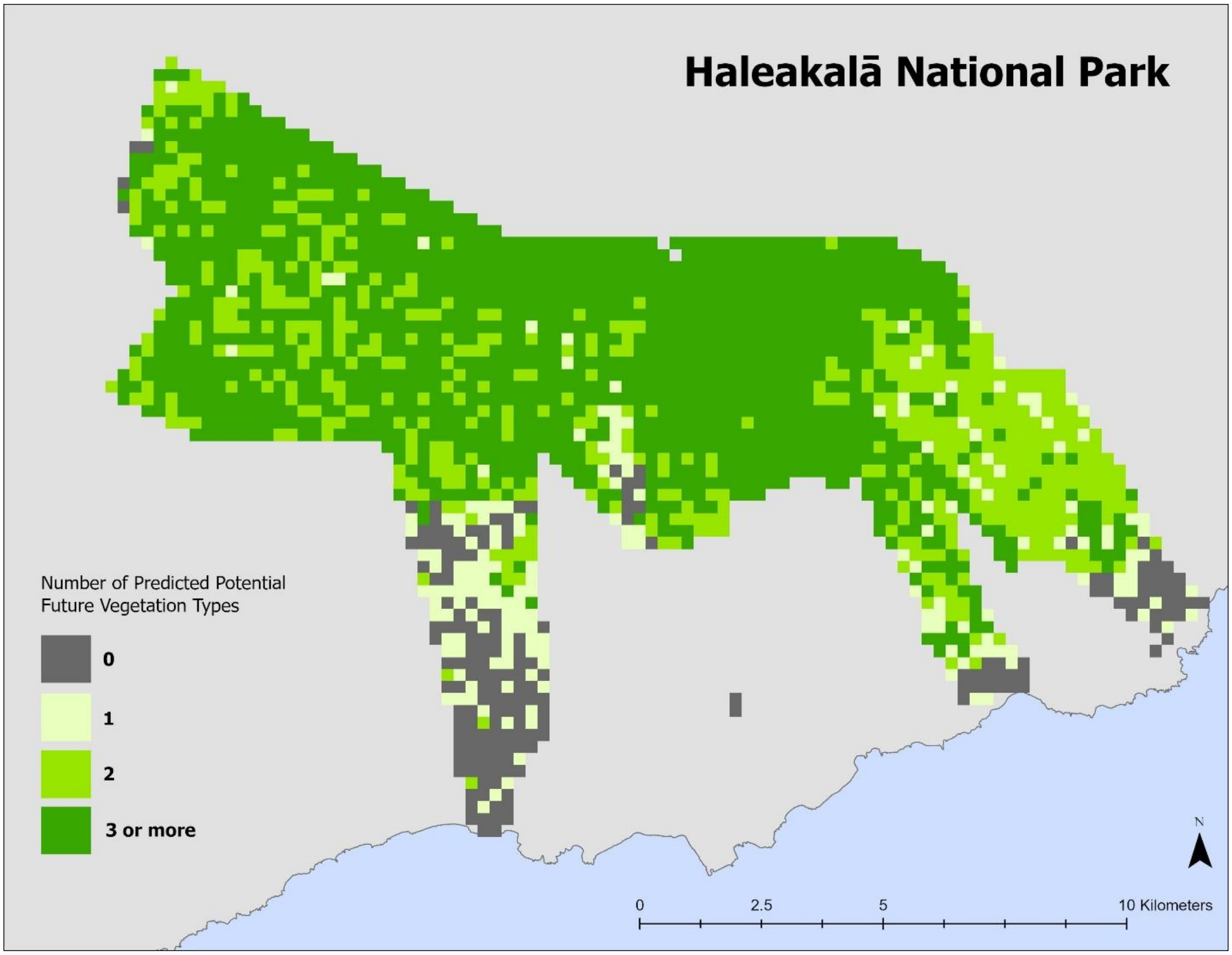

Figure 20: Number of predicted potential future vegetation types and distributions in Haleakala National Park (2100 estimate) by assessing product overlap using the Single-Category classification method.

Future research

Our study is the first of its kind to develop PVT models to examine the future climate vulnerability of native vegetation land cover types in protected areas by incorporating a bioclimatic variables dataset containing baseline and end-of-century climate projections for the Hawaiian Islands. While our research has provided a foundational understanding of potential methods for assessing vegetation distribution changes in the context of climate change, there are many avenues for future research that are critical towards developing this knowledge further. Remote sensing of land surface temperature, precipitation, and cloud cover should be examined for all PAs to identify significant changes along a time series (e.g. BFAST models) and used to validate the trend or trajectory of our NCAR model along with other single or ensembled models. The Breaks for Additive Seasonal and Trend (BFAST) framework (Verbesselt et al. 2010) has been used to detect vegetation changes, including forest disturbances and NDVI response to drought, with minimal influence from seasonal amplitudes and in spite of time series irregularity (DeVries et al. 2015; Forkel et al. 2013; Xu et al. 2020). Field methods that can be used to measure, monitor, and validate anticipated vegetation change in the Hawaiian Islands include the over 300 sites from the United States Geological Survey's Forest Inventory and Analysis (FIA) program (Tinkham et al. 2018) and the OpenNahele, a community-level forest plot database for the Hawaiian Islands (Craven et al. 2018).

However, our study has successfully mapped potential expansion and contraction of ranges for each native vegetation category, determined areas of suitability overlap, and highlighted areas that are clearly anticipated to change in response to climate by the end of the century. While some regions are anticipated to convert from one vegetation type to another (Figures 15-16) or have suitability for multiple vegetation types (Figure 14), there are other regions found in our study that are anticipated to decrease in native vegetation or increase in areas that previously weren't suitable. For this reason, rather than conducting field surveys over a wide area, our recommendations are to focus on the highlighted areas with a high predicted vegetation change to conduct selective field surveys and validate the model over time.

Aside from surveying field sites, the utilization of remote sensing methods may also prove useful in validating our results. In order to identify vegetation change you have to know the species composition, structure, and function of native vegetations types. Some vegetation changes are easily to quantify such as bare area into grasslands or grassland into forest. However, identifying changes from native wet forest to mesic forest on the Hawaiian Islands or migration in highly fragments native dry forests are difficult using remote sensing.

Over the last two decades, there has been a rapid evolution in spaceborne remote sensing sensors, methods and techniques that have changed the way we measure and monitor vegetation types. Measuring includes identifying the x, y location of field plots, delineating vegetation types, and collecting metrics on a vegetation type. Monitoring is the use of time series spaceborne data to study dynamics over time and this has significant applications for vegetation change and conservation. Indeed, we can now collect real time remote sensing data on temperature, precipitation, fire, vegetation productivity, phenology, and health (Table 9). These metrics can be used to validate climate models and changes in native vegetation type function.

	Metric	Units	Pixel size	Sensors
Climate				
	Precipitation	cm	10 km	GPM
	Land surface temper.	degrees C	1 km, 100 m	MODIS, Landsat
	Cloud cover	%	1 km, 100 m	MODIS, Landsat
Vegetation				
	Primary Productivity	g C m^{-2} yr^{-1}	500 m	MODIS
	Photosynthetic activity	-1 to 1	4 m to 500 m	DOVE, MODIS
	Canopy cover tree	%	30 m	Landsat
	Leaf Area Index	1 to 6	300 m, 1 km	Sentinel 2
	Canopy height	m	10 m, 30 m	GEDI, Landsat
	Above ground biomass	Mg ha^{-1}	250 m	MODIS
	Phenology	leaf off, leaf on dates	20 m, 30 m	Sentinel, Landsat
Soils				
	Albedo	%	20 m, 30 m	Sentinel, Landsat

Table 9. Metrics that can be examined over randomized points or field plots within native Hawaiian vegetation types to identify changes in vegetation over time

There are several standard 2D metrics that can be quantified for a Hawaiian native vegetation type monitored since 2000 (Table 9). There are several continuous or gradient satellite-derived measures of two-dimensional vegetation such as fraction of absorbed photosynthetically active radiation (FPAR), net primary productivity, leaf area index (LAI), above-ground biomass, percent vegetation cover (Running et al. 2004, Skidmore et al. 2021). Using our randomized point locations for each native vegetation type time, series data on productivity, phenology, biomass, and percent vegetation cover since 2000 using Landsat (30 m) and 2016 using Sentinel (10 m) in GoogleEarh Engine. Identifying predicted vegetation migration and change should be easy (if ANOVA’s results say significantly different like climate metrics), and locations with a high probability of vegetation change can be closely examined for species and vegetation growth or mortality (due to heat or water stress).

There are also recent 3D spaceborne datasets that quantify the three-dimensional structure of vegetation or the vertical arrangement of canopy layers and plants life forms such as maximum, mean canopy height, and standard deviation (Lang et al. 2023). Recently, spaceborne data from the Global Ecosystem Dynamics Investigation (GEDI) on the International Space Station offer an unprecedented opportunity for studying biodiversity at lower latitudes. GEDI has three lasers which produce full waveforms within a 25 m circular footprint that can measure the 3-dimensional structure of forests and terrain. Each footprint is separated by 60 m along track, with an across-track distance of approximately 600 m between each of the eight tracks. GEDI covers areas between 51°North and South latitude and gathers data for approximately 4% of the earth's surface (Dubayah et al. 2020). More recently, GEDI has provided high-resolution lidar data on the Earth's forests and topography (Dubayah et al. 2020). GEDI data has been combined with Landsat to produce global canopy height models at 30 m spatial resolution (RMSE = 7-9 m) (Potapov et al. 2021) and Sentinel to produce 10 m spatial resolution (Lang et al. 2023) global canopy height models. This raw lidar and modelled vegetation structure data can be used as benchmarks for vegetation structure and associated native vegetation type into the future and could be used to identify change in native vegetation types.

Additionally, our research still lacks certainty regarding the effectiveness of our climate model inputs with regards to predicting vegetation change. To tackle this uncertainty, the next research steps would utilize a variety of different downscaled climate model inputs to recreate the process for single category and multi-category vegetation analysis, in order to determine trends and similarities as well as changes in accuracy that may result from the varying climate inputs. We would also recreate the same methodology by implementing the NCAR RCP 8.5 model with baseline and future projections going into 2040 and 2050 in order to determine the model with the most statistically likely outcome and highest performance. By modeling into the middle of the century, we are also able to see a mid-way change and get a better understanding of our vegetation trajectory and anticipated shifts over time. These mid-century predictions are also expected to be less extreme than our end of century projections and may prove easier to validate over time using a combination field and remote sensing methods. Ultimately, by projecting these changes at multiple time intervals, we can better understand the association between climate patterns and suitable native vegetation ranges, meaning that we are therefore able to validate more extreme anticipated trends if the projections of mid-century scenarios prove to be accurate and consistent with what is seen in the field.

Beyond our current scope of research, it is critical to highlight the valuable applications of this research towards unprotected or ambiguous areas across Hawaii that are affected by climate change. Climate change is anticipated to increase the frequency and severity of natural disasters in Hawaii, particularly wildfires and floods (Nugent et al. 2020). Rising temperatures, prolonged droughts, and altered precipitation patterns are contributing to conditions conducive to the ignition and spread of wildfires. In particular, the combination of dry vegetation, heightened temperatures, and reduced rainfall is creating an environment where wildfires can spread more rapidly across both native forests and grasslands (Trauernicht 2019). These fires pose significant threats to biodiversity, human infrastructure, and the economy, particularly in areas where development encroaches upon vulnerable ecosystems. In addition to wildfires, climate change is also expected to intensify the occurrence of extreme weather events, such as heavy rainfall and flash floods (Xue et al. 2020). These floods not only endanger human populations but also cause extensive damage to agricultural lands, infrastructure, and fragile ecosystems, further complicating efforts for recovery and resilience building across the islands (Storlazzi et al.

2024). Understanding climate trends under multiple end of century projections may better equip this region for a variety of anticipated natural disasters, and is therefore a valuable asset in the context of risk assessment and emergency preparedness in addition to environmental conservation and regulation.

While our research focused on protected areas across the islands of Hawaii, we must recognize that the impacts of climate change on vegetation across non-protected areas are substantial. Native plant species, many of which are uniquely adapted to the islands' specific climatic conditions, are increasingly vulnerable to the stresses imposed by rising temperatures, altered rainfall patterns, and more frequent extreme weather events (Shilsky 2000). In non-protected areas, where human activity such as urban development, agriculture, and tourism already contributes to habitat degradation, these changes exacerbate the loss of native vegetation (Barton et al. 2021). Invasive species, which tend to be more resilient to fluctuating climatic conditions, are likely to expand their range, outcompeting native plants and altering ecosystem structure and function (Vorsino et al. 2014). This vegetation loss not only threatens the integrity of Hawaii's ecosystems but also disrupts key ecological processes, including water retention and soil stabilization, making these areas more prone to erosion, landslides, and flood events (Nugent et al. 2020).

Research on climate change and vegetation dynamics in Hawaii offers significant translational value for broader environmental management and conservation efforts. By examining the specific impacts of climate change on Hawaii’s unique ecosystems, researchers can identify effective strategies for managing and conserving native plant species, particularly in regions vulnerable to invasive species and habitat degradation. The insights gained from these studies can be applied to other island ecosystems or coastal regions facing similar climate-related challenges. Furthermore, the development of adaptive management strategies, such as targeted invasive species control and ecosystem restoration, has the potential to mitigate the ecological and socio-economic impacts of climate change in Hawaii and beyond. This research thus serves not only to inform localized conservation efforts but also to contribute to expanded strategies for enhancing ecosystem resilience, mitigating natural disaster risks, and promoting sustainable land and water management practices across the pacific islands.

Conclusion

Understanding the relationship between future climate and vegetation vulnerability can prove to be vital for land management and conservation efforts as we plan to allocate resources towards areas that are most severely affected by climate change. Our study is the first of its kind to examine the future climate vulnerability of native vegetation land cover types in protected areas by utilizing a bioclimatic variables dataset containing baseline and end-of-century (NCAR RCP 8.5) climate projections for the Hawaiian Islands. We assessed seven native vegetation types (Native Dry Forest, Native Dry Shrub, Native Mesic Forest, Native Mesic Grassland, Native Mesic Shrub, Native Wet Forest, and Native Wet Shrub) using data provided by the Carbon Assessment of Hawaii (Jacobi et al. 2017). Our results determined there are statistically significant differences for almost all pairwise comparisons of the selected native vegetation types in relation to baseline annual precipitation means and annual temperature means. Additionally, our study outlined a new methodology for a multi-category classification approach as well as an individualized single category classification approach to determine potential future vegetation distributions under the NCAR RCP 8.5 climate scenario using Random Forest. Agreement between both methods found that across the entire archipelago, Native Dry Shrub is anticipated to experience the greatest contraction in range followed by Native Wet Forest, while Native Mesic Forest is anticipated to experience the greatest expansion in range, followed by Native Mesic Shrub. We also utilized the single category classification method to determine anticipated overlap for native vegetation suitability, and found that across our study area, 33.27% of the area has no overlap and predicts no suitability for any of the vegetation types while 12.75% of the area has a predicted future suitability for one vegetation type. Alternatively, 20.70% of the area across the islands predicted future suitability for various combinations of two vegetation types, and 33.28% predicted future suitability for combinations of 3 or more vegetation types. Overall, we found that the multi-category classification model had a higher classification accuracy compared to the individualized approach, however the multi-category classification approach results in an exclusionary determination of vegetation type for each pixel, whereas the individualized approach allows for overlap and may be useful for highlighting regions that can sustain two or more vegetation types in the future.

This research has the potential to provide critical updates for stakeholders and climate investigators who aim to protect native vegetation that is at risk. Today, with less than 0.2% of the land area of the United States, the Hawaiian Islands hold more than a third of the nation's entire listing of endangered and threatened species under the U.S. Endangered Species Act (Gustafson et al. 2014). The evolutionary history and geographic isolation of the Hawaiian Islands have predisposed the flora to characteristics of distribution, population structure, and reproduction that have inherently produced fragile conditions for species survival. This aspect of isolation can be readily seen, as it applies to geographic range and habitat occurrence. Among endemic flowering plant species in the Hawaiian Islands, 68% have a range restricted to a single island, and 78% of species exhibit relatively narrow ranges of habitat distribution (Gustafson et al. 2014). Protection of native vegetation is a priority because native forests in Hawaii are ecologically and culturally valuable plant species more likely to support endemic bird and insect populations (Tsang et al. 2019).

Over the next decades the Hawaiian flora and fauna are expected to be impacted by changes in temperature, precipitation, and sea level (Eversole 2014). The flora of the Hawaiian Islands is undergoing significant extinctions; 134 endemic plants are considered extinct or extinct in the wild (Wood et al. 2019). Thirty-seven percent of the extant endemic or 33% of the native flora (454 taxa) are listed as threatened or endangered under the U.S. Endangered Species Act (USFWS 2021) and the State of Hawaii, and many species are still lacking assessments. Despite these and other examples, rigorous research detailing the specific impacts of climate change on Hawaiian terrestrial ecosystems is still sparse. At this point in time, research and monitoring resources are too sparse to substantially advance our understanding of the ecological impacts of climate change on this intricate island system without a rigorous concerted effort.

Appendix

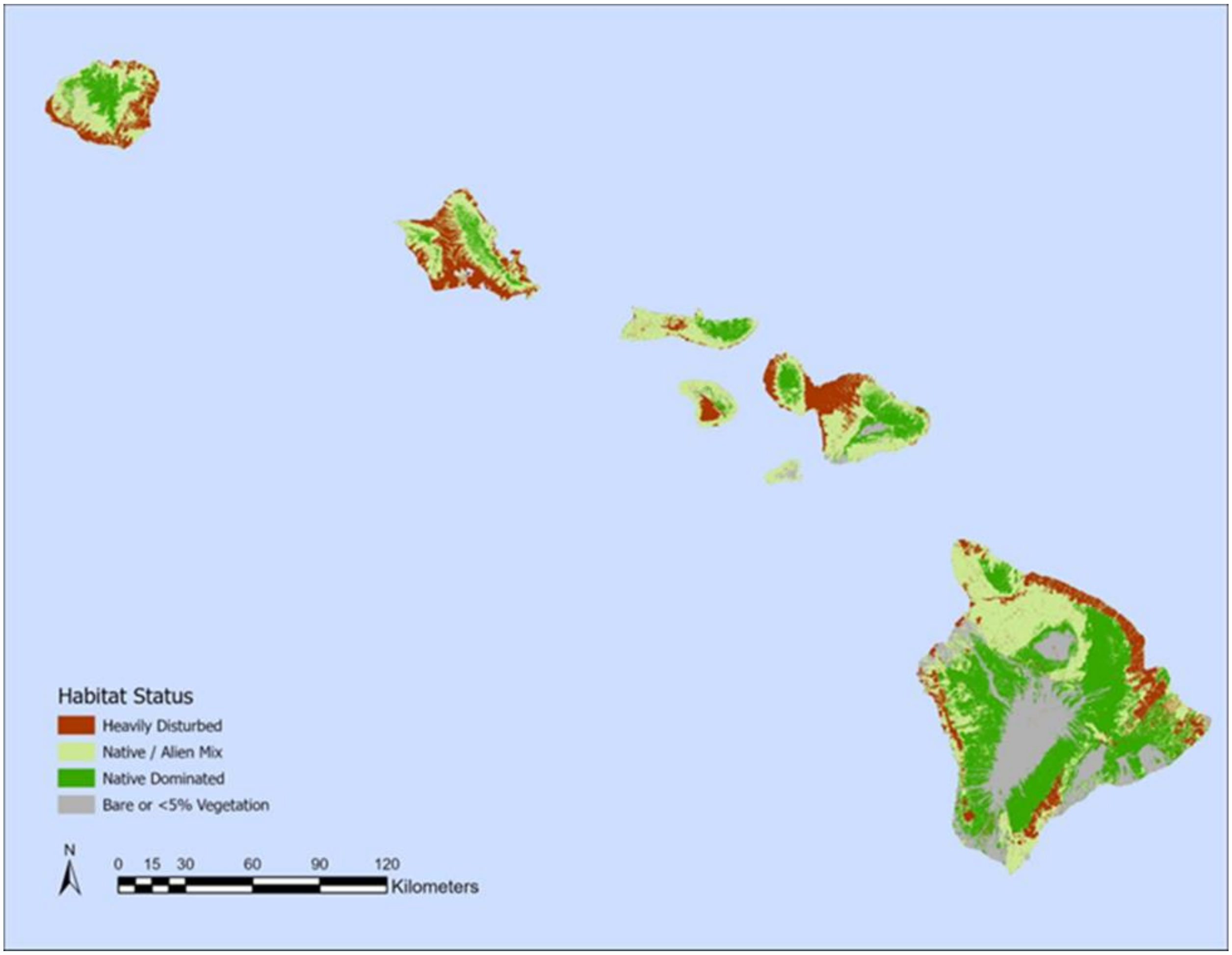

Figure 1A: Depicts the status, or degree of disturbance, to plant communities on the main Hawaiian Islands utilizing the Carbon Assessment of Hawaii Habitat Status Map (2017).

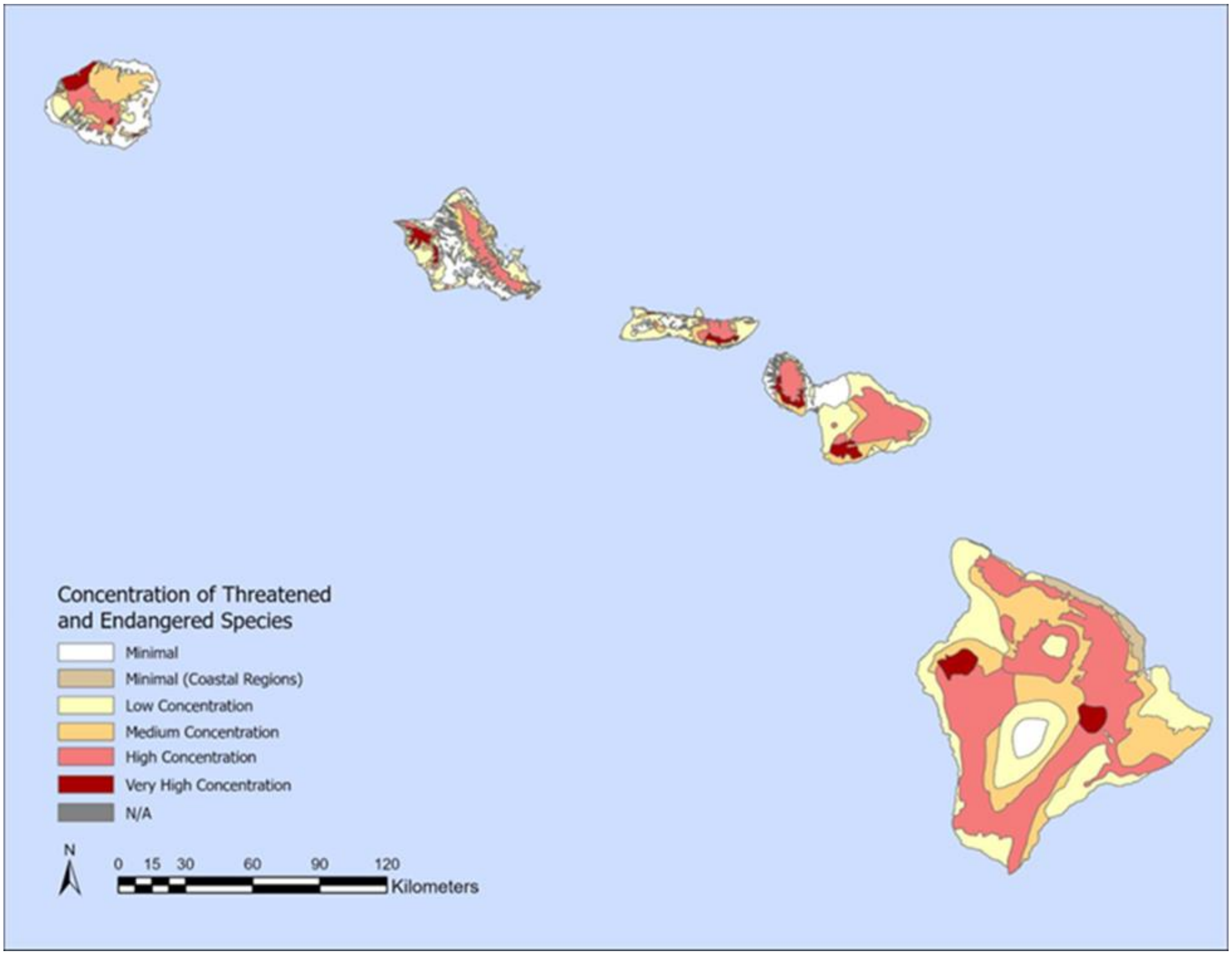

Figure 1B: Concentration of Threatened and Endangered Plant Species on the main Hawaiian Islands. All island coverages were digitized from Division of Forestry and Wildlife's mylar threatened and endangered plant species maps. DOFAW's maps were created using The Nature Conservancy's Rare & Endangered Species maps. Digitized by the Office of Planning from source described above, March 1992.

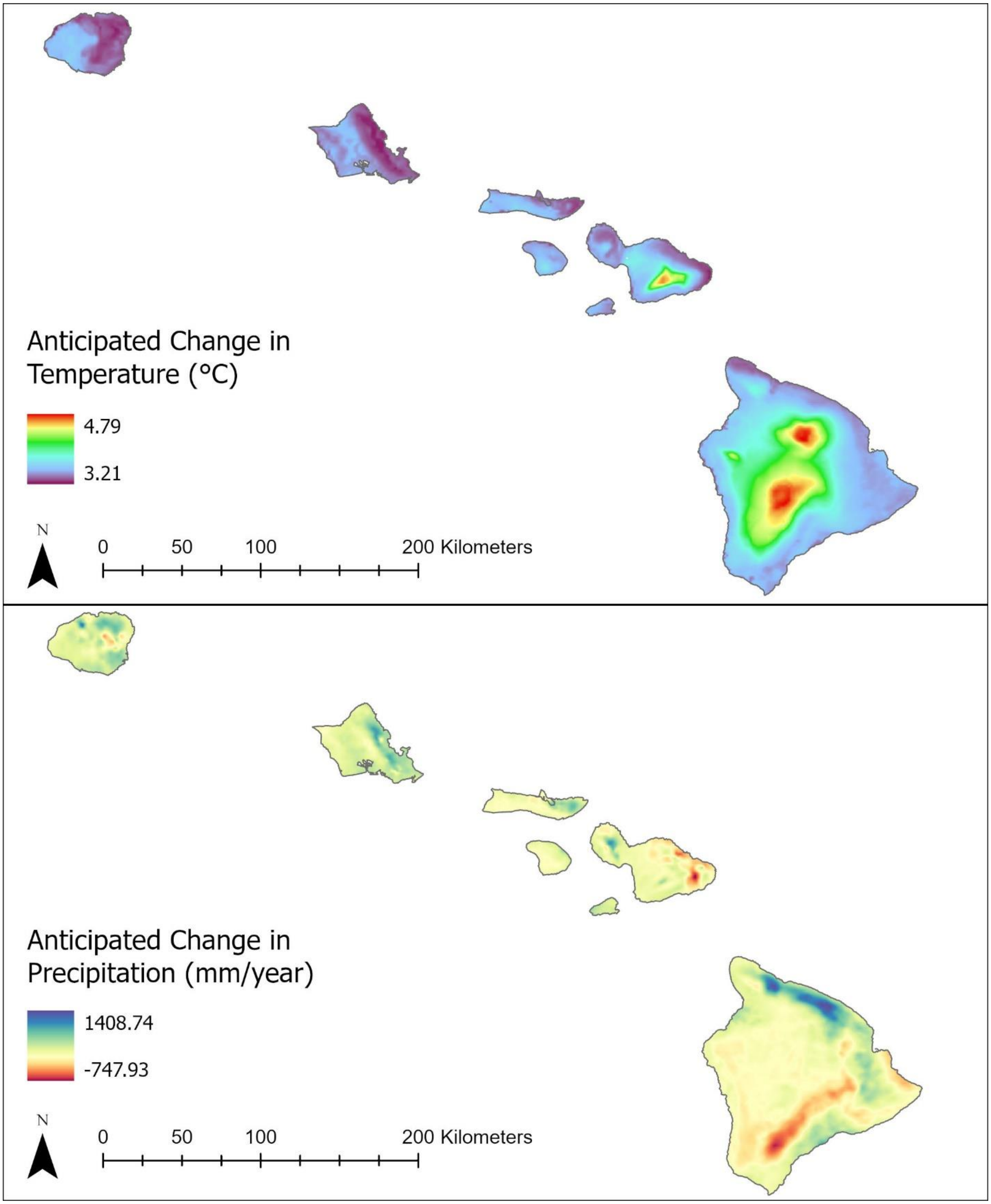

Figure 2A: Anticipated Change in Temperature and Precipitation across the Hawaiian Islands by the year 2100, NCAR RCP 8.5 Climate Projection

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