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Geospatial Approaches to Biodiversity Monitoring: Applications in Hawaiʻi

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Geospatial Approaches to Biodiversity Monitoring: Applications in Hawai‘i

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by

Monica J. Dimson

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ABSTRACT OF THE DISSERTATION

Geospatial Approaches to Biodiversity Monitoring:
Applications in Hawai‘i

by

Monica J. Dimson
Doctor of Philosophy in Geography
University of California, Los Angeles, 2022
Professor Thomas Welch Gillespie, Chair

Human activity continues to drive global biodiversity change and loss. Comprehensive biodiversity monitoring is critical to evaluating and informing conservation policy and management, and diverse data sources that can enhance the spatial and temporal coverage of conventional field monitoring are needed. In this dissertation, I explore the potential contributions of broad-scale, publicly accessible geospatial datasets to biodiversity monitoring in the Hawaiian Islands. This region supports exceptional levels of endemism but continues to experience significant native habitat loss. Non-native plant species outnumber the native flora, and ecosystems like tropical dry forest are unlikely to recover without active restoration.

Though citizen science data are abundant, they are often collected opportunistically, and potential biases must be understood before utilizing observations. I examined citizen science participation patterns from 2008-2021 using over 93,000 species observations from iNaturalist. The majority of observations were made by visitors to Hawaii, who were more likely to access remote locations and make research-grade observations. However, during the COVID-19 pandemic, visitor activity declined significantly, demonstrating the importance of sustained, local participation for consistent monitoring. I then evaluated the utility of iNaturalist in invasive plant monitoring, and found that non-native species represented a high proportion of iNaturalist plant observations. Comparison of iNaturalist and professional agency observations for four example invasive species showed that iNaturalist data were biased toward accessible, disturbed sites, and professional data toward less accessible, native-dominated sites. Habitat suitability models built with the two datasets often produced distinct results, whereas combining the data provided a more comprehensive estimate of invasive species habitat. Finally, I used a Landsat Normalized Difference Vegetation Index (NDVI, a proxy of vegetation productivity) time series to evaluate changes in dry forest from 1999-2022. Despite regional declines in rainfall, native and restored dry forest NDVI increased during this period. Previous, coarser-scale studies have reported negative NDVI trends in the region, but Landsat resolution or finer is better suited to capturing conditions in fragmented dry forests and monitoring progress at restoration sites. Together, these studies illustrate the value of utilizing and integrating multiple, complementary data sources to improve the breadth and continuity of biodiversity monitoring.

The dissertation of Monica J. Dimson is approved.

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Glen Michael MacDonald

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University of California, Los Angeles

2022

For my dad, Cesar Abaya Dimson,

who taught me everything of consequence

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Dimson, M.*, & Gillespie, T. W. (2020). Trends in active restoration of tropical dry forest: Methods, metrics, and outcomes. *Forest Ecology and Management*, *467*, 118150.

Dimson, M.*, Lynch, S. C., & Gillespie, T. W. (2019). Using biased sampling data to model the distribution of invasive shot-hole borers in California. *Biological Invasions*, *21*(8), 2693-2712.

Choe, D. H., Campbell, K., Hoddle, M. S., Kabashima, J., Dimson, M.*, & Rust, M. K. (2018). Evaluation of a hydrogel matrix for baiting western yellowjacket (Vespidae: Hymenoptera). *Journal of Economic Entomology, 111*(4), 1799-1805.

Eatough Jones, M., Kabashima, J., Eskalen, A., Dimson, M.*, Mayorquin, J. S., Carrillo, J. D., Hanlon, C. C., & Paine, T. D. (2017). Evaluations of insecticides and fungicides for reducing attack rates of a new invasive ambrosia beetle (*Euwallacea* sp., Coleoptera: Curculionidae: Scolytinae) in infested landscape trees in California. *Journal of Economic Entomology, 110*(4), 1611-1618.

Rust, M. K., Choe, D. H., Wilson-Rankin, E., Campbell, K., Kabashima, J., & Dimson, M.* (2017). Controlling yellow jackets with fipronil-based protein baits in urban recreational areas. *International Journal of Pest Management, 63*(3), 234-241.

Dimson, M.*, Baldwin, R. A, & Quinn, N. (2016). User-Friendly Resource Design: Providing Accessible Ground Squirrel Extension for the Web. *Proceedings of the Vertebrate Pest Conference*, 27.

DIGITAL PUBLICATIONS

Dimson, M.*, Harrigan, R., & Gillespie, T. W. (2020). Biodiversity Atlas of Los Angeles. www.biodiversityla.org

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Chapter 1. Introduction

Anthropogenic activity continues to drive global biodiversity loss and change. Habitat fragmentation and loss, climate change, pollution, and species invasions have led to substantial declines in ecosystem functioning, in turn compromising the provision of essential ecosystem services (Isbell et al., 2017). Biodiversity monitoring is critical to the effective implementation and evaluation of biodiversity policy and environmental management. Yet few coordinated national or global monitoring systems exist, and explicit monitoring targets are often lacking in policy and program design, including in the UN Convention on Biological Diversity post-2020 global biodiversity framework (Lindenmayer et al., 2012; Perino et al., 2022).

The collection of high-quality species data is a perpetual challenge in conservation biogeography (Richardson & Whittaker, 2010). Formal, systematic surveys are resource-intensive and therefore often limited in geographic or temporal extent (Hochachka et al., 2012), restricting the utility of the data in broad-scale conservation planning or applications such as habitat suitability modeling (Meyer et al., 2016). Monitoring has been particularly deficient in regions of high species endemism and for invertebrates, plants, and fungi (Hochkirch et al., 2021). Invasive species have been notably neglected, despite being a major driver of biodiversity loss, and existing databases remain difficult to access, share, and integrate (Foxcroft et al., 2017; Reaser et al., 2020; Wallace et al., 2020). In ecological restoration—a valuable and increasingly necessary component of biodiversity management—monitoring has been rare or insufficient, and an unfortunate emphasis is placed on short-term, potentially misleading results due in part to the perceived costliness of monitoring activities (Stanturf et al., 2014).

It has been widely acknowledged that diverse data streams are needed to improve our understanding of biodiversity trends (Perino et al., 2022; Richardson & Whittaker, 2010).

Integrating data sources can yield spatial, temporal, or taxonomic complementarity in biodiversity monitoring, while increasing longevity and resilience during periods of sociopolitical instability (Kühl et al., 2020). For example, lockdowns during the COVID-19 pandemic, which halted human mobility (as well as regular research activities) in an unprecedented way, highlighted the gaps in current field-monitoring programs (Bates et al., 2020). Perino et al. (2022) highlighted several opportunities for enhancing monitoring capacity, including citizen science monitoring networks and advancements in remote sensing methods.

Citizen science, often defined as public participation in the collection or processing of scientific data, has supported several long-term, large-scale monitoring programs that have been used to inform environmental management and policymaking (Kühl et al., 2020). In addition to enabling data collection on scales that often exceed those of professional research, citizen science programs can increase participants' scientific literacy (Bonney et al., 2016) and improve trust between professional scientists, natural resource managers, and the public (Vann-Sander et al., 2016). In biodiversity citizen science, participants often record species observations and a number of attributes, including location data. Programs vary greatly in scale and structure, which typically has consequences for data quality (Freitag et al., 2016). Formalized structures entail more rigorous, standardized data collection that could potentially deter participants. Low-structure programs are often more accessible, but lead to uneven, opportunistic sampling and thus observations that are biased in space, time, or taxonomically. Because the majority of observations are produced by the latter (Di Cecco et al., 2021), it is necessary to investigate and understand sampling bias patterns so that citizen science data can be meaningfully used.

Remote sensing provides consistent, repeatable measurements over large spatial extents, and remotely-sensed variables can be used to map species, habitats, and functional or spectral diversity (Wang & Gamon, 2019). Though issues of data access and affordability have limited the use of remote sensing products to some extent, the value of remote sensing in biodiversity monitoring has long been recognized (e.g. the Essential Biodiversity Variables framework). It has the potential to enhance invasive species mapping (Foxcroft et al., 2017) as well as augment and improve the efficiency of conventional in situ forest restoration monitoring (de Almeida et al., 2020). Satellite systems like Landsat and Sentinel-2 offer long archives at site-level spatial resolutions that can be accessed on a number of platforms, whereas application of products from Light Detection and Ranging (LiDAR) methods, despite their promise in monitoring canopy structure, is constrained by cost and availability.

The goal of this dissertation was to explore the utility of large-scale, public geospatial datasets in monitoring biodiversity in the Hawaiian Islands. Formed by volcanic hot spots nearly 4,000 kilometers away from the nearest continent, Hawaii is the world's most isolated archipelago and supports a wide range of habitats across elevation and moisture gradients (Fleischer et al., 1998). The native flora of Hawaii is derived from approximately 270 wind-, water-, and bird-dispersed original colonizing species (Price, 2004), and is currently estimated to include over 1,300 vascular plants, 90% of which are endemic to one or more islands (Imada, 2012). Today, however, native Hawaiian plants are outnumbered by non-native species whose introduction can be linked to two main waves of human colonization. Beginning in 1000-1200 AD, Polynesian settlers introduced many non-native crop plants that they cultivated in extensive agricultural systems, clearing and greatly altering Hawaii's lowland vegetation (Cuddihy & Stone, 1990; Kirch, 2011). Over two dozen Polynesian introductions still occur in Hawaii. European colonists first arrived in the early 18th century, but it was during the mid-19th century, following the Great Māhele of 1848, that rapid, large-scale land changes began taking place

(Cuddihy & Stone, 1990). Forest clearance for commercial agriculture, cattle ranching, and logging expanded, particularly in dry habitats (Price, 2004), and the rate of non-native introductions increased, eventually totaling over 5,000 species and varieties (Nagata, 1985).

Due to the combination of high rates of endemism and significant native vegetation loss, Hawaii has been included in the Polynesia-Micronesia biodiversity hotspot (Myers et al., 2000) (Figure 1.1). The impacts of deforestation and species invasions persist long after fields and pastures are abandoned. Many non-native plant species are now naturalized, with self-sustaining populations, while others have become highly invasive and pose significant threats to native ecosystems by disrupting native plant regeneration, limiting resource acquisition, and altering wildfire regimes (Cuddihy & Stone, 1990; Ellsworth et al., 2014). Hawaii's native plants, having evolved in isolation, without herbivores, and largely without broad-scale disturbances like wildfire, are highly vulnerable to displacement by invasive species (Gillespie et al., 2008). Much of the land area of the main Hawaiian Islands is now dominated by non-native vegetation (42-99%) (Hughes et al., 2017), and Hawaii has the highest rates of species extinction and endangerment in the United States (Sakai et al., 2002). Native ecosystem recovery thus requires intensive, active restoration and continuous monitoring (Dimson & Gillespie, 2020).

The guiding questions of this dissertation are:

1. How has participation in low-structure citizen science in Hawaii varied in space and over time?
2. Does low-structure citizen science increase the extent of non-native plant monitoring in Hawaii, and, consequently, contribute to improved estimates of invasive plant habitat?
3. How can site-level, remotely sensed indices be used to enhance monitoring of tropical dry forest fragments and restoration sites?

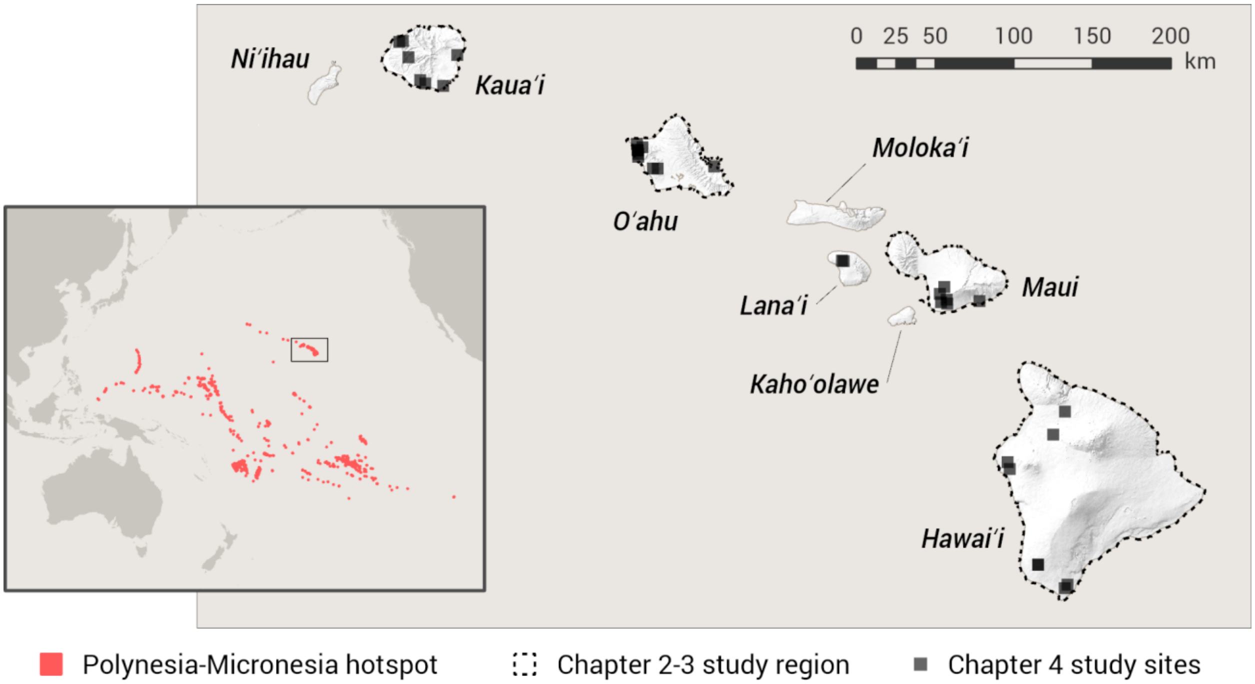


Figure 1.1
The study area of the dissertation included islands in the younger, southeastern range of the Hawaiian archipelago, which is part of the Polynesia-Micronesia biodiversity hotspot (inset adapted from Myers et al., 2000; hillshade layer from State of Hawaii Office of Planning).

Each question is addressed in one of the following three chapters of the dissertation. Chapter 2, **Who, where, when: Observer behavior influences spatial and temporal patterns of iNaturalist participation**, uses observation trends on the iNaturalist citizen science platform to examine who tends to participate in low-structure biodiversity citizen science, where observations tend to be made, and how this has changed over time, particularly after COVID-19 lockdowns were instated. Chapter 3, **Citizen science enhances invasive plant monitoring and estimates of habitat**, focuses on sampling biases in non-native plant observations from iNaturalist. Using four example invasive species, I compare the environmental distribution of iNaturalist data to professional data from regional management agencies in Hawaii, and build a series of habitat suitability models with each dataset. In Chapter 4, **Landsat NDVI time series capture greening trends in Hawaiian dry forest**, I use a common remote sensing vegetation index to observe changes in native species-dominated, non-native species-dominated, and actively restored (or in-progress) dry forest sites in order to assess the utility of open access Landsat imagery in increasing the longevity and frequency of ecosystem monitoring.

While each chapter focuses on regions of or sites in the Hawaiian Islands (Figure 1.1), the iNaturalist and Landsat datasets have global spatial coverage. Management implications are discussed that may be applicable in other regions where conventional field survey data are scarce. The studies in this dissertation illustrate potential applications for freely accessible datasets in monitoring biodiversity, and demonstrate the value of utilizing multiple, complementary data sources to expand the breadth and continuity of monitoring.

References

Bates, A. E., Primack, R. B., Moraga, P., & Duarte, C. M. (2020). COVID-19 pandemic and associated lockdown as a "Global Human Confinement Experiment" to investigate biodiversity conservation. *Biological Conservation*, *248*, 108665. doi:10.1016/j.biocon.2020.108665

Cuddihy, L. W., & Stone, C. P. (1990). *Alteration of native Hawaiian vegetation: Effects of humans, their activities and introductions*. University of Hawaii, Cooperative National Park Resources Studies Unit. https://pcsuhawaii.org/books-1990/

de Almeida, D. R. A., Stark, S. C., Valbuena, R., Broadbent, E. N., Silva, T. S. F., de Resende, A. F., Ferreira, M. P., Cardil, A., Silva, C. A., Amazonas, N., Zambrano, A. M. A., & Brancalion, P. H. S. (2020). A new era in forest restoration monitoring. *Restoration Ecology*, *28*(1), 8–11. doi:10.1111/rec.13067

Di Cecco, G. J., Barve, V., Belitz, M. W., Stucky, B. J., Guralnick, R. P., & Hurlbert, A. H. (2021). Observing the Observers: How Participants Contribute Data to iNaturalist and Implications for Biodiversity Science. *BioScience*, *71*(11), 1179–1188. doi:10.1093/biosci/biab093

Dimson, M., & Gillespie, T. W. (2020). Trends in active restoration of tropical dry forest: Methods, metrics, and outcomes. *Forest Ecology and Management*, *467*, 118150. doi:10.1016/j.foreco.2020.118150

Ellsworth, L. M., Litton, C. M., Dale, A. P., & Miura, T. (2014). Invasive grasses change landscape structure and fire behaviour in Hawaii. *Applied Vegetation Science*, *17*(4), 680–689. doi:10.1111/avsc.12110

Fleischer, R. C., Mcintosh, C. E., & Tarr, C. L. (1998). Evolution on a volcanic conveyor belt: Using phylogeographic reconstructions and K–Ar-based ages of the Hawaiian Islands to estimate molecular evolutionary rates. *Molecular Ecology*, *7*(4), 533–545. doi:10.1046/j.1365-294x.1998.00364.x

Foxcroft, L. C., Pyšek, P., Richardson, D. M., Genovesi, P., & MacFadyen, S. (2017). Plant invasion science in protected areas: Progress and priorities. *Biological Invasions*, *19*(5), 1353–1378. doi:10.1007/s10530-016-1367-z

Freitag, A., Meyer, R., & Whiteman, L. (2016). Strategies Employed by Citizen Science Programs to Increase the Credibility of Their Data. *Citizen Science: Theory and Practice*, *1*(1), 2. doi:10.5334/cstp.6

Gillespie, T. W., Chu, J., & Pau, S. (2008). Non-native plant invasion of the Hawaiian Islands. *Geography Compass*, *2*(5), 1241–1265. doi:10.1111/j.1749-8198.2008.00152.x

Hochkirch, A., Samways, M. J., Gerlach, J., Böhm, M., Williams, P., Cardoso, P., Cumberlidge, N., Stephenson, P. J., Seddon, M. B., Clausnitzer, V., Borges, P. A. V., Mueller, G. M., Pearce-Kelly, P., Raimondo, D. C., Danielczak, A., & Dijkstra, K. B. (2021). A strategy for the next decade to address data deficiency in neglected biodiversity. *Conservation Biology*, *35*(2), 502–509. doi:10.1111/cobi.13589

Hughes, R. F., Asner, G. P., Litton, C. M., Selmants, P. C., Hawbaker, T. J., Jacobi, J. D., Giardina, C. P., & Sleeter, B. M. (2017). Influence of Invasive Species on Carbon Storage in Hawaiʻi's Ecosystems. In *Baseline and Projected Future Carbon Storage and Carbon Fluxes in Ecosystems of Hawaiʻi* (pp. 43–55).

Imada, C. (2012). *Hawaiian Native and Naturalized Vascular Plants Checklist* (Bishop Musem Technical Report 60). Bishop Museum.

Isbell, F., Gonzalez, A., Loreau, M., Cowles, J., Díaz, S., Hector, A., Mace, G. M., Wardle, D. A., O'Connor, M. I., Duffy, J. E., Turnbull, L. A., Thompson, P. L., & Larigauderie, A. (2017). Linking the influence and dependence of people on biodiversity across scales. *Nature*, *546*(7656), 65–72. doi:10.1038/nature22899

Kirch, P. V. (2011). When did the Polynesians settle Hawaii? A review of 150 years of scholarly inquiry and a tentative answer. *Hawaiian Archaeology*, *12*, 3–26.

Kühl, H. S., Bowler, D. E., Bösch, L., Bruelheide, H., Dauber, J., Eichenberg, David., Eisenhauer, N., Fernández, N., Guerra, C. A., Henle, K., Herbinger, I., Isaac, N. J. B., Jansen, F., König-Ries, B., Kühn, I., Nilsen, E. B., Pe'er, G., Richter, A., Schulte, R., … Bonn, A. (2020). Effective Biodiversity Monitoring Needs a Culture of Integration. *One Earth*, *3*(4), 462–474. doi:10.1016/j.oneear.2020.09.010

Lindenmayer, D. B., Gibbons, P., Bourke, M., Burgman, M., Dickman, C. R., Ferrier, S., Fitzsimons, J., Freudenberger, D., Garnett, S. T., Groves, C., Hobbs, R. J., Kingsford, R. T., Krebs, C., Legge, S., Lowe, A. J., Mclean, R., Montambault, J., Possingham, H., Radford, J., … Zerger, A. (2012). Improving biodiversity monitoring. *Austral Ecology, 37*(3), 285–294. doi:10.1111/j.1442-9993.2011.02314.x

Myers, N., Mittermeier, R. A., Mittermeier, C. G., da Fonseca, G. A. B., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, *403*(6772), 853–858. doi:10.1038/35002501

Nagata, K. M. (1985). Early Plant Introductions in Hawai'i. *Hawaiian Journal of History*, *19*, 35–61.

Perino, A., Pereira, H. M., Felipe-Lucia, M., Kim, H., Kühl, H. S., Marselle, M. R., Meya, J. N., Meyer, C., Navarro, L. M., van Klink, R., Albert, G., Barratt, C. D., Bruelheide, H., Cao, Y., Chamoin, A., Darbi, M., Dornelas, M., Eisenhauer, N., Essl, F., … Bonn, A. (2022). Biodiversity post-2020: Closing the gap between global targets and national-level implementation. *Conservation Letters, 15*(2). doi:10.1111/conl.12848

Price, J. P. (2004). Floristic biogeography of the Hawaiian Islands: Influences of area, environment and paleogeography: Floristic biogeography of the Hawaiian Islands. *Journal of Biogeography, 31*(3), 487–500. doi:10.1046/j.0305-0270.2003.00990.x

Reaser, J. K., Simpson, A., Guala, G. F., Morisette, J. T., & Fuller, P. (2020). Envisioning a national invasive species information framework. *Biological Invasions*, *22*(1), 21–36. doi:10.1007/s10530-019-02141-3

Richardson, D. M., & Whittaker, R. J. (2010). Conservation biogeography: Foundations, concepts and challenges. *Diversity and Distributions*, *16*(3), 313–320. doi:10.1111/j.1472-4642.2010.00660.x

Sakai, A. K., Wagner, W. L., & Mehrhoff, L. A. (2002). Patterns of Endangerment in the Hawaiian Flora. *Systematic Biology*, *51*(2), 276–302.

Stanturf, J. A., Palik, B. J., & Dumroese, R. K. (2014). Contemporary forest restoration: A review emphasizing function. *Forest Ecology and Management*, *331*, 292–323. doi:10.1016/j.foreco.2014.07.029

Wallace, R. D., Bargeron, C. T., & Reaser, J. K. (2020). Enabling decisions that make a difference: Guidance for improving access to and analysis of invasive species information. *Biological Invasions*, *22*(1), 37–45. doi:10.1007/s10530-019-02142-2

Wang, R., & Gamon, J. A. (2019). Remote sensing of terrestrial plant biodiversity. *Remote Sensing of Environment*, *231*, 111218. doi:10.1016/j.rse.2019.111218

Chapter 2. Who, where, when: Observer behavior influences spatial and temporal patterns of iNaturalist participation

This chapter has been submitted in its current form to *Applied Geography* as Dimson, M. and Gillespie, T.W. Who, where, when: Observer behavior influences spatial and temporal patterns of iNaturalist participation. *Applied Geography* (*in revision*). Supplementary materials for this chapter are provided in Appendix A.

Abstract

Citizen science can expand professional biodiversity monitoring through the contributions of volunteers. Lockdowns during the COVID-19 pandemic, however, impacted participation in various ways. We investigated how observer behaviors and spatial biases influenced iNaturalist participation in the Hawaiian Islands from 2008-2021. Overall, participation grew exponentially until 2019, then decreased after implementation of COVID-19 travel restrictions. Sampling was consistently biased toward developed areas, sites near roads or trails, and areas with fewer protections, while Hawaii's most diverse and remote habitats tended to be underrepresented. Observer behaviors, defined by activity level and primary location (i.e. Hawaii resident or visitor), were associated with different sampling patterns. The decrease in 2020 was largely driven by a decline in visitors, who represented nearly two-thirds of participants, were generally more active, and made more research-grade observations. Meanwhile, resident observers continued to participate at relatively steadier rates, but tended to be short-term participants and more restricted to human-impacted landscapes. The majority and spatial diversity of observations therefore relied on the participation of a small fraction of observers, most of whom were unlikely

to live in the region. Fostering sustained participation from local communities could improve the consistency and quality of iNaturalist monitoring data and thus its utility in biodiversity conservation.

2.1. Introduction

Biodiversity citizen science is a significant source of the broad-scale species data needed to inform conservation science and policymaking (McKinley et al., 2017; Theobald et al., 2015). Citizen science is public participation in the collection or processing of scientific data, often in collaboration with professional scientists (Kullenberg & Kasperowski, 2016). In addition to enabling data collection on scales that often exceed those of professional researchers, citizen science programs can increase participants' scientific literacy (Bonney et al., 2016), improve trust between professional scientists, natural resource managers, and the public (Vann-Sander et al., 2016), and confer mental health benefits through purposeful, outdoor activities for participants (Coventry et al., 2019).

The tradeoff between citizen science program structure and participant engagement often has consequences for data quality or credibility (Freitag et al., 2016). More formal structures have protocols that standardize data collection, but may be less approachable for participants, while low-structure programs attract more participants but often result in opportunistic observations. Uneven sampling effort can result in biased data and produce skewed estimates of biodiversity. Several sampling biases have been documented in citizen science data, including taxonomic biases (Boakes et al., 2016; Mair & Ruete, 2016) and spatial biases toward protected areas (Botts et al., 2011; Tulloch et al., 2013), sites with open water (Boakes et al., 2016), and areas with a higher human footprint, such as population centers, parks, agriculture, and roadsides

(Geldmann et al., 2016; Lloyd et al., 2020; Mair & Ruete, 2016; Pernat et al., 2021). These data quality issues may discourage professional scientists from using or acknowledging citizen science sources (Riesch & Potter, 2014; Theobald et al., 2015; Vann-Sander et al., 2016). However, similar biases have been recorded in data collected by professionals (Boakes et al., 2010; Martin et al., 2012; Meyer, Weigelt, & Kreft, 2016), and the quality of biased data can be significantly improved by collecting information about the observation process (Kelling et al., 2019). For example, species distribution modeling studies have demonstrated that estimates of observer expertise or survey effort can be used to mitigate bias (Johnston et al., 2021; Steen et al., 2019; van Strien et al., 2013). It is thus important to characterize observer behavior to the extent possible, particularly when utilizing data from low-structure programs that contribute the majority of citizen science observations (Di Cecco et al., 2021).

In spring 2020, lockdown measures were implemented across the globe in an attempt to slow the spread of SARS-CoV-2 coronavirus and prevent significant loss of human life. These necessary restrictions constrained human mobility in an unprecedented way, and, by limiting regular research activities, highlighted the importance of considering diverse data streams like citizen science for monitoring biodiversity (Bates et al., 2020). Several papers have examined how citizen science participation changed during COVID-19 lockdowns. Participation decreased during the City Nature Challenge in Tokyo (Kishimoto & Kobori, 2021) and for several programs in the United States (Crimmins et al., 2021), but remained steady in programs in Colombia (Sánchez-Clavijo et al., 2021), Australia (Stenhouse et al., 2022), and Italy, Spain, and the United Kingdom (Basile et al., 2021). However, even if the overall number of observations was consistent with previous years, a relative increase in urban activity was sometimes observed, indicating a potential loss of data in natural areas (Basile et al., 2021; Crimmins et al., 2021;

Sánchez-Clavijo et al., 2021). Additionally, Kishimoto & Kobori (2021) found steadier participation among more enthusiastic observers, and Crimmins et al. (2021) observed that though total observations were less impacted during lockdowns, fewer participants were active. In short, citizen science participation in many regions became spatially restricted to more accessible sites, and was sustained by relatively smaller groups of more active observers. The latter may be concerning if we wish to broaden participation in and build more inclusive citizen science communities, which are often disproportionately white and/or male (Cooper et al., 2021; Pateman et al., 2021; Sánchez-Clavijo et al., 2021). Understanding the impact of COVID-19 restrictions on participation is important for data users, but is also an opportunity to explore who participates in citizen science and where.

This study examined changes in iNaturalist participation in the Hawaiian Islands from 2008 to 2021. Located in the Polynesia-Micronesia biodiversity hotspot, a region of exceptional species endemism as well as ongoing habitat loss (Myers et al., 2000), the Hawaiian Islands are a unique place to examine trends in citizen science biodiversity monitoring as well as the effects of COVID-19 protocols. The region relies heavily on tourism as a source of income and employment (Agrusa et al., 2021) and received over 10.2 million visitors in 2019, i.e. seven times as many visitors as residents (Chun et al., 2019). Yet as the world's most geographically isolated archipelago (Fleischer et al., 1998), travel to the islands could be feasibly restricted during the COVID-19 pandemic, coinciding with a 73.9% decrease visitor arrivals in 2020 (Chun et al., 2020). The primary restriction was a 14-day quarantine for travelers to Hawaii, instated on March 17, 2020 (Office of the Governor, 2020a). Quarantine requirements were adjusted amid developments in testing, vaccination, and new variants, and ultimately lifted on July 8, 2021 for fully vaccinated, domestic travelers (Office of the Governor, 2021). A state-by-state analysis by Crimmins et al. (2021) noted significantly fewer iNaturalist observations and active observers in Hawaii than expected in spring 2020. As previous studies have demonstrated, this decrease in participation likely varied in space and among participants.

Our analysis investigated how iNaturalist participation trends from 2008 to 2021 were influenced by observer behavior (characterized by participants' primary location and activity level) and anthropogenic site attributes that often affect sampling, including land cover, proximity to roads and trails, and land designation. Our primary research questions were: 1) How do observer behaviors influence iNaturalist participation patterns in Hawaii? 2) Are iNaturalist observations spatially biased toward human-impacted landscapes, and does sampling bias vary according to observer behavior? 3) How have spatial and observer behavior trends varied over time, particularly before and after the implementation of COVID-19 travel restrictions?

2.2. Materials and methods

2.2.1. iNaturalist observations and attributes

iNaturalist is a popular, web-based citizen science platform and joint initiative of the California Academy of Sciences and the National Geographic Society that aims to connect participants to nature while producing scientifically valuable biodiversity data. The app has an unstructured survey format that makes it possible for users of any experience level to post species observations from their smartphone or computer. Observations are therefore largely opportunistic, but abundant; over 87 million have been made by over 2.5 million users since the program's launch in 2008 (iNaturalist, 2022b).

From the iNaturalist website (www.inaturalist.org), we downloaded georeferenced observations made in Hawaii (place_id=11) between 01-01-2008 and 12-31-2021. Our analysis included 93,160 observations with some level of taxonomic identification, a positional accuracy of ≤ 30 meters, and coordinates within the land area of Hawaii's six largest islands (Hawaiʻi, Maui, Oʻahu, Kauaʻi, Molokaʻi, and Lānaʻi; access to and iNaturalist data for Niʻihau and Kahoʻolawe being limited). We did not include observations with obscured locations in this analysis. iNaturalist automatically obscures coordinates for threatened, endangered, and other at-risk taxa, and observers may also choose to obscure locations of observations made at their homes. The removal of these records could potentially result in spatial bias as well, but this is not possible to confirm given that the true coordinates are obscured within a 0.2 x 0.2 degree cell.

Each observation was classified by quality and taxonomic group. For the quality classes, we used iNaturalist's Data Quality Assessment statuses: research-grade, needs ID, and casual. Research-grade observations are dated, georeferenced, non-captive records uploaded with a photo or sound, whose identification has been agreed upon by 2/3 of iNaturalist identifiers. Needs ID refers to observations that possess research-grade criteria but have not yet been identified. Observations lacking any of the research-grade criteria are classified as casual.

Taxonomic groups included amphibians, birds, fishes, fungi, invertebrates, mammals, plants and algae, and reptiles. Classification was based primarily on the iconic_taxa iNaturalist attribute. Observations for which iconic_taxa=NA were manually classified using the scientific or common name information provided. Protozoa represented a small percentage of observations in the study extent (<0.001%) and were excluded from analysis.

2.2.2. Defining observer behavior

Variables used to define observer primary location and activity level were derived from observations made in Hawaii from 2008-2021 (i.e. regardless of accuracy, species identification, etc.) and additional data acquired through the Observation Histogram operation in the iNaturalist

Application Program Interface version 1.3.0 (https://api.inaturalist.org). This operation yields the unique dates that a user was active and the number of observations they made that day.

As location information is not available for iNaturalist observers, we inferred primary location from the proportion of each individual's activity in Hawaii. We scored activity in Hawaii on a scale of 0 to 1 as: $h = 0.4(o_h) + 0.6(d_h)$, where o_h is the proportion of observations the observer made in Hawaii, and d_h is the proportion of all active days (unique dates on which an observer recorded at least one observation on the app) that they made an observation in Hawaii from 2008-2021. For $h > 0.5$, the observer was classified as likely to be *resident* (hereafter, '*residents*'). Otherwise, they were considered likely to be *visiting* (hereafter, '*visitors*'). While this classification method is limited by the assumption that the majority of an observer's activity will occur where they live, it is better suited to an isolated region like Hawaii, which has clear geophysical boundaries and to which travel requires a substantial investment of time and resources. Previous studies have also shown that citizen science participants are typically active closer to home (Dennis & Thomas, 2000; Farias et al., 2022; Gratzer & Brodschneider, 2021; McGoff et al., 2017).

Three engagement metrics were used to define activity level. *Activity ratio* is the observer's active days divided by their active period (date of their first observation minus date of last observation, in days) (Ponciano & Brasileiro, 2014). *Relative activity duration* is the ratio of the observer's active days to total days in our study period (i.e. 01-01-2008 to 12-31-2021) (Boakes et al., 2016). Activity ratio describes how engaged an observer was while active on the app, while relative activity duration describes their engagement relative to other iNaturalists. Lastly, the *total number of observations* made by each observer provides a measure of the extent of their engagement (Boakes et al., 2016). This last metric was normalized using a natural log transformation given that values were highly skewed, then scaled to span 0 to 1 like the other two metrics.

To group observers by these metrics, we used a clustering analysis approach similar to that of Boakes et al. (2016) and Ponciano & Brasileiro (2014). We began by identifying a suitable number of clusters with Ward's minimum variance, a bottom-up hierarchical clustering analysis that requires no predefined number of clusters (k). We then calculated Average Silhouette Width (ASW) with the pamk() function in the R package *cluster* to test the strength of the clustering structure for $k = 2$ through 10. ASW ranges from -1 to 1; we selected k with ASW > 0.51, which indicates a reasonable structure has been found (Struyf et al., 1996). Using this k value, we partitioned observers into activity levels using K-means clustering, a centroid-based, unsupervised algorithm that classifies data into a pre-defined number of clusters. A random number of centroids is given at the start, and data points are assigned to their closest centroid in order to form k groups.

2.2.3. Spatial attributes

We examined the spatial distribution of iNaturalist activity by land cover, land designation, and distance to roads and trails. Activity was measured by number of observations and number of visits by unique observers. Land cover was derived from the Carbon Assessment of Hawaii Land Cover map (Jacobi et al., 2017) by reclassifying the biome_unit attribute into eight general classes (Table 2.1a). Land designation was based on Gap Analysis Project (GAP) status codes for areas in the U.S. Geological Survey Protected Areas Database (U.S. Geological Survey Gap Analysis Project, 2018), (Table 2.1b). GAP codes serve as a measure of management intent to conserve biodiversity. Though protected areas are often well-sampled by citizen science (Stenhouse et al., 2022; Tulloch et al., 2013), the distribution of participant activity may be influenced by infrastructure and management at a given site (Walden-Schreiner et al., 2018). To calculate distance to roads and trails, we compiled a vector layer using U.S. Census Bureau TIGER/Line Shapefiles for all roads in Hawaii, the Na Ala Hele Trail system (State Department of Land and Natural Resources, DOFAW, updated 2018), and AllTrails, a web and mobile outdoor recreation app for sharing trail information. We included 135 heavily trafficked AllTrails routes with at least 100 reviews that were not already accounted for in the Na Ala Hele system. Euclidean distance to road/trail was calculated across a 30-meter resolution raster that matched the extent and resolution of the land cover layer. This grid was divided into quartiles to create four classes (Table 2.1c).

Observations were assigned to spatial classes via the Spatial Join tool in ArcMap 10.7 or the extract() function in the R package *raster*. Statistical significance of bias was estimated by comparing the observed distribution of observations or unique observers to the expected distribution, assuming that the probability of occurrence in a given spatial class is proportional to the area that the class occupies. We use the index from Kadmon et al. (2004): $Bias_d = (n_d - p_d N) / \sqrt{p_d(1 - p_d)N}$, where n_d is the number of observations or observers per class d, p_d is the probability that the observation or observer is located in class d given its area, and N is the total number of possible observations or observers. Values are distributed like a standard normal variable (Z) and statistically significant ($\alpha = 0.05$) for values greater than 1.64. We calculated spatial bias in observations and unique observers per year and for the entire study period.

Table 2.1
Descriptions of land cover (a), land designation (b), and distance to road/trail (c) classes and the proportion of the study area each class occupies.

a) Land cover	Description	% Area
Developed	Low to high intensity development; developed open space	6.3%
Agriculture	Cultivated agriculture; plantation forests	7.3%

	Bare ground	Very sparse vegetation to unvegetated areas	19.0%
	Grassland	Native and alien dry, mesic, and wet grasslands	16.9%
	Dry/mesic shrubland	Dry and mesic shrublands; coastal strand vegetation	14.1%
	Dry/mesic forest	Dry and mesic forests	15.3%
	Wet forest/shrubland	Wet forests, shrublands, ferns, and cliff communities	21.0%
	Wetland/water	Native bogs, wetlands, and water	0.2%
b)	Land designation	Description	% Area
	None	Area is not included in the USGS Protected Areas Database	46.4%
	Limited protection	Protected area with no known mandates to prevent natural habitat conversion (GAP status 4)	17.5%
	Multi-use	Some protection from habitat conversion, but multiple extractive uses permitted (e.g. logging, mining, off-highway vehicle recreation) (GAP status 3)	20.4%
	For biodiversity	Area has permanent protection from natural habitat conversion (GAP status 1 or 2)	15.8%
c)	Distance to road/trail	Description	% Area
	Q1	≤ 150 meters	25.3%
	Q2	≤ 553.2 meters	24.9%
	Q3	≤ 1513.4 meters	24.9%
	Q4	> 1513.4 meters	25.0%

2.2.4. Participation over time

Pre-COVID growth in iNaturalist participation (2008 to 2019) was estimated using linear models of observations, unique observers, and new observers (i.e. first-time participants in Hawaii) versus year. Participation metrics were log transformed (ln *x*) to improve fit and distribution of residuals. Analysis of covariance (ANCOVA) was used to test for significant differences in growth among observer behavior, observation quality, taxonomic, and spatial classes. To determine whether participation varied by quarter (January-March (JFM), April-June (AMJ), July-September (JAS), October-December (OND)), we first used ANCOVA to check for significant differences among quarterly regression slopes. As quarter did not have a significant effect, linear models were fitted with annual data. ANCOVA assumptions were checked using Shapiro-Wilk normality tests and Bartlett tests of homogeneity of variances. When ANCOVA indicated significant differences for a given factor, post-hoc interaction analysis was performed using the emtrends() function in the R package *emmeans*.

The effect of travel restrictions in 2020-2021 was evaluated in two ways. Expected values for 2020-2021 participation metrics were predicted using annual and quarterly 2008-2019 linear models. We then calculated the difference between the observed and predicted values in each quarter, and determined significance using predicted 95% confidence intervals (Crimmins et al., 2021). Second, we calculated percent change in participation metrics from 2019 to 2020 and 2021 on annual and quarterly bases. We calculated overall percent change as well as change within each observer behavior, observation quality, taxonomic, and spatial class.

2.3. Results

2.3.1. Observer behavior

The clustering analysis included 10,265 iNaturalist observers who had made at least one observation meeting spatial and taxonomic requirements (section 2.2.2). Though Average Silhouette Width was higher for $k = 2$ (0.70) than $k = 3$ (0.58), $k = 2$ only distinguished the least active observers. We thus chose 3 clusters in order to describe more variation in activity: *enthusiastic*, *moderate,* and *short-term*. Enthusiastic observers made relatively high numbers of observations (median = 601) and had the highest mean relative activity duration (63.3% of the study period). Short-term observers made the fewest observations (median = 2) and had high activity ratios (median = 1) because they were only active on the app for an average of 1.7 days. The moderate group represented activity in between these two extremes (median = 20 observations/observer) and included the majority of observers.

Observers likely to be Hawaii residents represented 36.7% of participants, and nearly half (49.0%) were classified as short-term (Figure 2.1). The majority of enthusiastic observers were classified as visitors, while only 4.1% were residents. Enthusiastic observers from either location represented just 14.1% of all participants but made 47.9% of observations. Enthusiastic observers were the most likely to make research-grade observations, while short-term observers were the least likely (Table 2.2). Only 52.1% of short-term observers made at least one research-grade observation, compared to 77.0% of moderate and 95.0% of enthusiastic observers. Most residents were short-term, and were thus more likely to make casual observations (50.5% of residents submitted at least one casual observation, versus 35.5% of visitors).

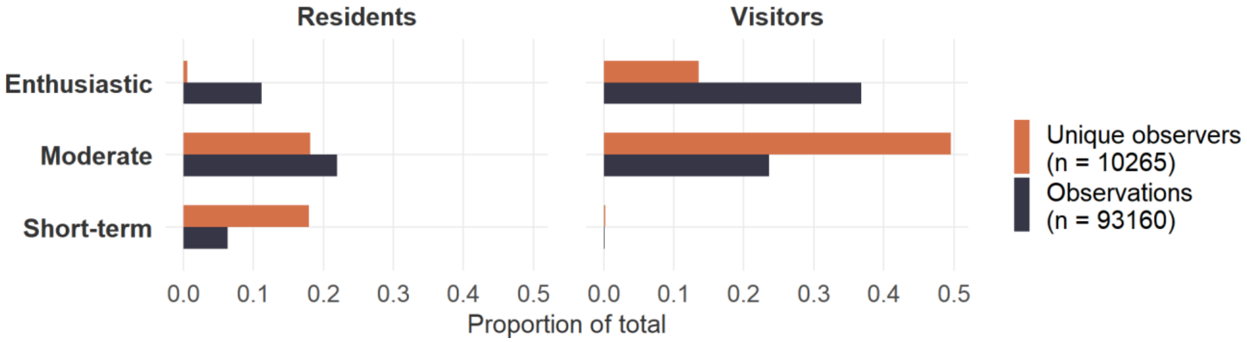


Figure 2.1
Proportion of unique observers and observations per observer behavior, as defined by location (resident or visitor in Hawaii) and activity level (enthusiastic, moderate, or short-term).

Visiting-short-term observers were most likely to equally split their activity between Hawaii and elsewhere (Appendix A, Figure A1). It is thus possible that some short-term observer locations were misclassified; for instance, a one-time observer who was visiting Hawaii during their brief active period on the app would be classified as resident. However, the low number of visiting-short-term observers that we identified was a logical outcome of classification given that citizen scientists more often participate close to where they live.

Most observers only recorded one taxonomic group (Table 2.2), which was typically plants and algae. Plants and algae represented the majority of observations in every observer behavior class, at least 51.3% (visiting-enthusiastic observers) and as much as 75.9% (resident-short-term observers) (Appendix A, Figure A2). Birds and invertebrates were the next most-observed taxonomic groups among all observers. Mammals and amphibians were the least likely to be observed. Taxonomic diversity was highest in observations made by resident-enthusiastic observers, who were most likely to record multiple groups (Appendix A, Figure A3).

Table 2.2
Sampling characteristics of individual observers, including the quality of the observations they recorded and the number of taxonomic groups or spatial classes they sampled at least once. Values provided are the mean and standard deviation of each observer behavior class.

	Resident - Enthusiastic	Resident - Moderate	Resident - Short-term	Visiting - Enthusiastic	Visiting - Moderate	Visiting - Short-term
Observation quality						
% research-grade	64.9 (23.2)	47.2 (34.2)	37.6 (42.4)	76.6 (27.6)	60.4 (40.6)	37.5 (45.4)
% needs ID	25.4 (19.7)	26.5 (29.4)	28.9 (39.9)	15.7 (22.5)	18.3 (31.4)	16.3 (33.9)
% casual	9.8 (14.9)	26.2 (32.2)	33.5 (42.8)	7.7 (18.2)	21.3 (34.8)	46.2 (49.7)
# of taxonomic groups or spatial classes						
Taxonomic groups	4.7 (2.2)	1.9 (1.2)	1.2 (0.6)	2.7 (1.8)	1.6 (1)	1.3 (1.2)
Land cover classes	5.5 (2.2)	2.1 (1.4)	1.3 (0.7)	2.9 (2.1)	1.7 (1.2)	1.3 (1.2)
Land designation classes	3.2 (1)	1.7 (0.8)	1.1 (0.4)	2.1 (1.1)	1.4 (0.7)	1.2 (0.5)
Distance to road/trail classes	2.7 (1.2)	1.4 (0.7)	1.1 (0.4)	1.7 (1)	1.2 (0.5)	1.1 (0.3)

2.3.2. Overall spatial bias

iNaturalist activity was most strongly biased towards developed and wetland/water land cover types, non-designated sites, and sites within 150 meters of a road or trail (Figure 2.2). Wetland/water observations were primarily clustered in highly accessible, coastal sites. The most significantly underrepresented classes in terms of observations were grassland and wet forest/shrubland land cover types, areas managed for biodiversity, and sites further than 150 meters from roads and trails. These classes, except for grassland, were also where observers tended to be less active. Prior to 2016, there was greater spatial variability in sampling patterns.

But observations and unique observers have been consistently concentrated in certain sites, including those closest to roads and trails, in developed areas, and wetlands and open water, throughout the study period.

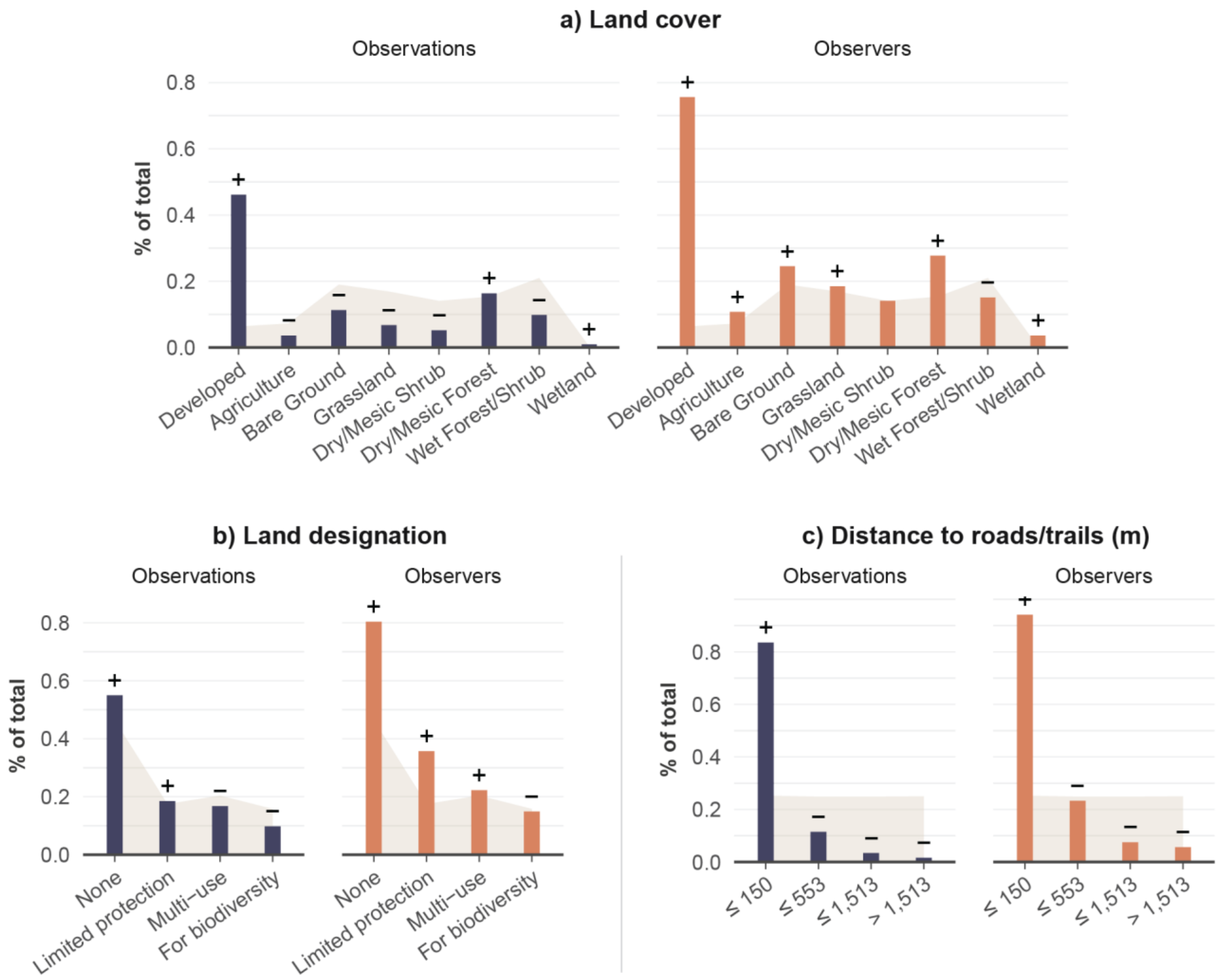


Figure 2.2
Sampling bias in iNaturalist observations and unique observer visits by a) land cover, b) land designation, and c) distance to road/trail. Gray area represents the percent area occupied by each class. +/- indicates significant over-/under-representation.

Overrepresentation of areas with a higher human impact (developed, more accessible, and non-designated) was strongest in casual observations, and relatively lower in observations made by visiting-enthusiastic observers. Enthusiastic observers, particularly residents, were more likely to sample a greater diversity of land cover types, land designations, and sites further from roads and trails than less active observers (Table 2.2). All taxonomic groups showed the same biases toward developed areas, non-designated sites, and sites closest to roads and trails, with a few exceptions. Bias toward developed sites was relatively lower among fishes and fungi, which were highly represented in coastal bare ground areas and dry/mesic forest, respectively. Fungi observations were also skewed toward multi-use areas.

2.3.3. Pre-COVID participation trend

We found statistically significant positive relationships ($p<0.001$) between year and observations, unique observers, and new observers from 2008-2019 (Appendix A, Table A1). Annual observations and unique observers increased in all observation quality, taxonomic, and spatial classes, with no significant differences among classes indicated by one-way ANCOVA.

Figure 2.3

Participation by observer location, estimated using linear models of log-transformed observations, unique observers, and new observers versus year. Participation among residents increased at a significantly higher rate than visitors from 2008-2019.

When observers were grouped by location only, all three variables increased at a higher rate among residents ($p<0.001$ for observations and unique observers; $p<0.01$ for new observers) (Figure 2.3). When grouped by location and activity, all observer behavior classes showed positive trends except for the visiting-short-term group, for which no significant relationship was detected. This is likely due to the low number of samples available for this group. One-way ANCOVA and post-hoc comparison of slopes showed that observations by resident-enthusiastic, resident-short-term, and visiting-moderate observers increased at a significantly higher rate than the visiting-enthusiastic group (Appendix A, Table A2). Annual increases in new and unique observers were significantly higher for resident-moderate, resident-short-term, and visiting-moderate observers than for both enthusiastic groups.

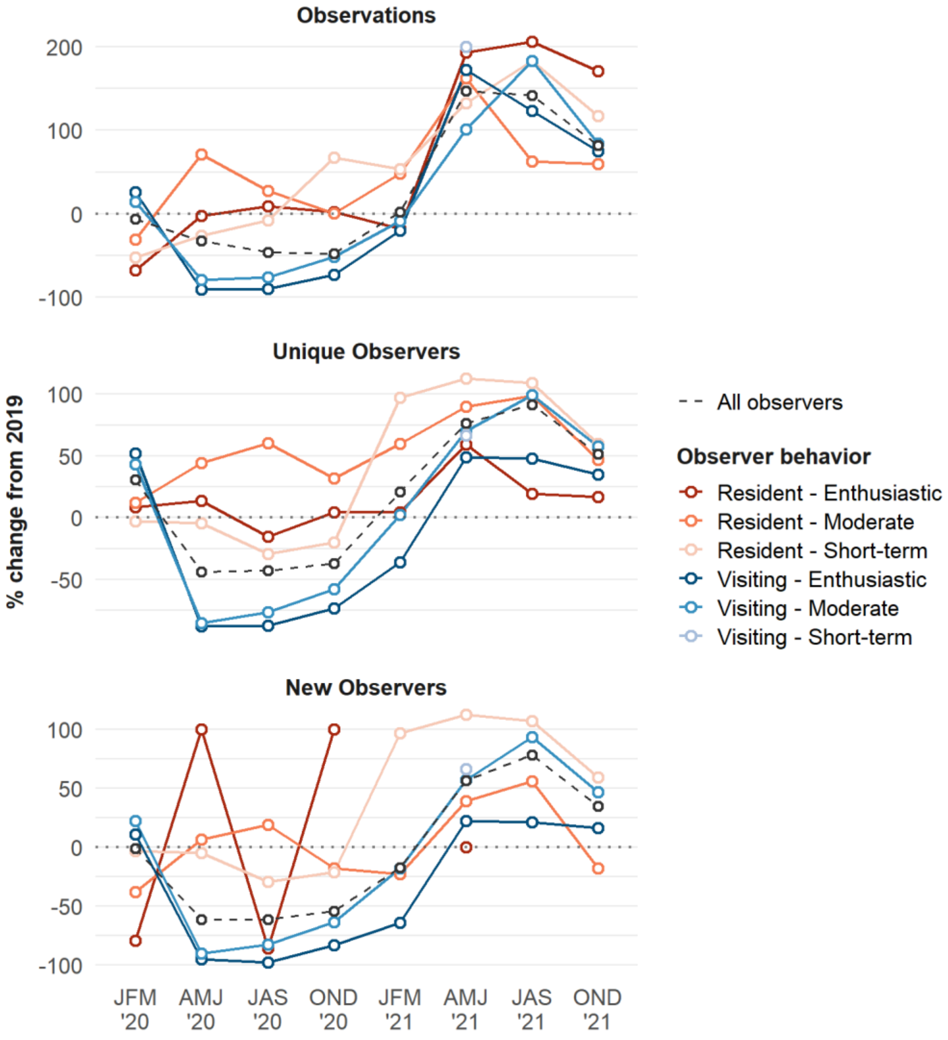
2.3.4. 2020-2021 changes in participation

Participation was lower than expected in AMJ, JAS, and OND 2020 (Appendix A, Tables A3-4). Observations, unique observers, and new observers were 32.4%, 33.2%, and 40.1% lower in 2020 than in 2019, respectively, with declines primarily occurring from AMJ to OND (Figure 2.4). From 2019 to 2020, decreases in needs ID and research-grade observations were double that of casual-grade, and the number of unique observers who made research-grade observations decreased by 37.1% (Appendix A, Figure A4). Among taxonomic groups, fishes and fungi were the least impacted in 2020 relative to 2019 (observations of fish increased by 2.8%), while birds and reptiles had the largest percent decreases in both observations and unique observers.

Visitors and residents showed distinct trends. In 2020, observations, unique observers, and new observers declined by 52.7%, 50.1%, and 64.2%, respectively, in the visiting-enthusiastic group and 47.3%, 52.3%, and 57.6% in the visiting-moderate group. Certain metrics were significantly lower than expected during the AMJ, JAS, and OND quarters (Figure 2.5). Resident participation was also lower than expected (with a few exceptions, see Figure 2.5), but to a lesser extent; participation in 2020 still exceeded that of 2019 during certain quarters (Figure 2.4) and for some groups, like resident-moderate observers (Appendix A, Figure A5).

Figure 2.4

Change in observations, unique observers, and new observers relative to 2019, shown for all observers (dashed line) and by observer behavior class (solid lines).



Spatial bias did not change significantly from 2019 to 2020, and activity in all spatial classes was less than expected (Appendix A, Tables A3-4). Relative changes in participation did vary somewhat among spatial classes. Compared to 2019, declines were less pronounced in agricultural land cover and more pronounced in dry/mesic shrubland (Appendix A, Figure A4). Areas managed for biodiversity experienced a larger decrease in observations from 2019 to 2020 compared to other land designation classes, particularly during AMJ. Certain changes only occurred during specific quarters: in AMJ 2020, bare ground sites saw a relative decrease in observations, and dry/mesic forest—a class usually sampled in proportion to its area—was significantly underrepresented. The magnitude of observation bias increased in developed areas during the AMJ and JAS quarters and in non-designated areas during AMJ 2020.

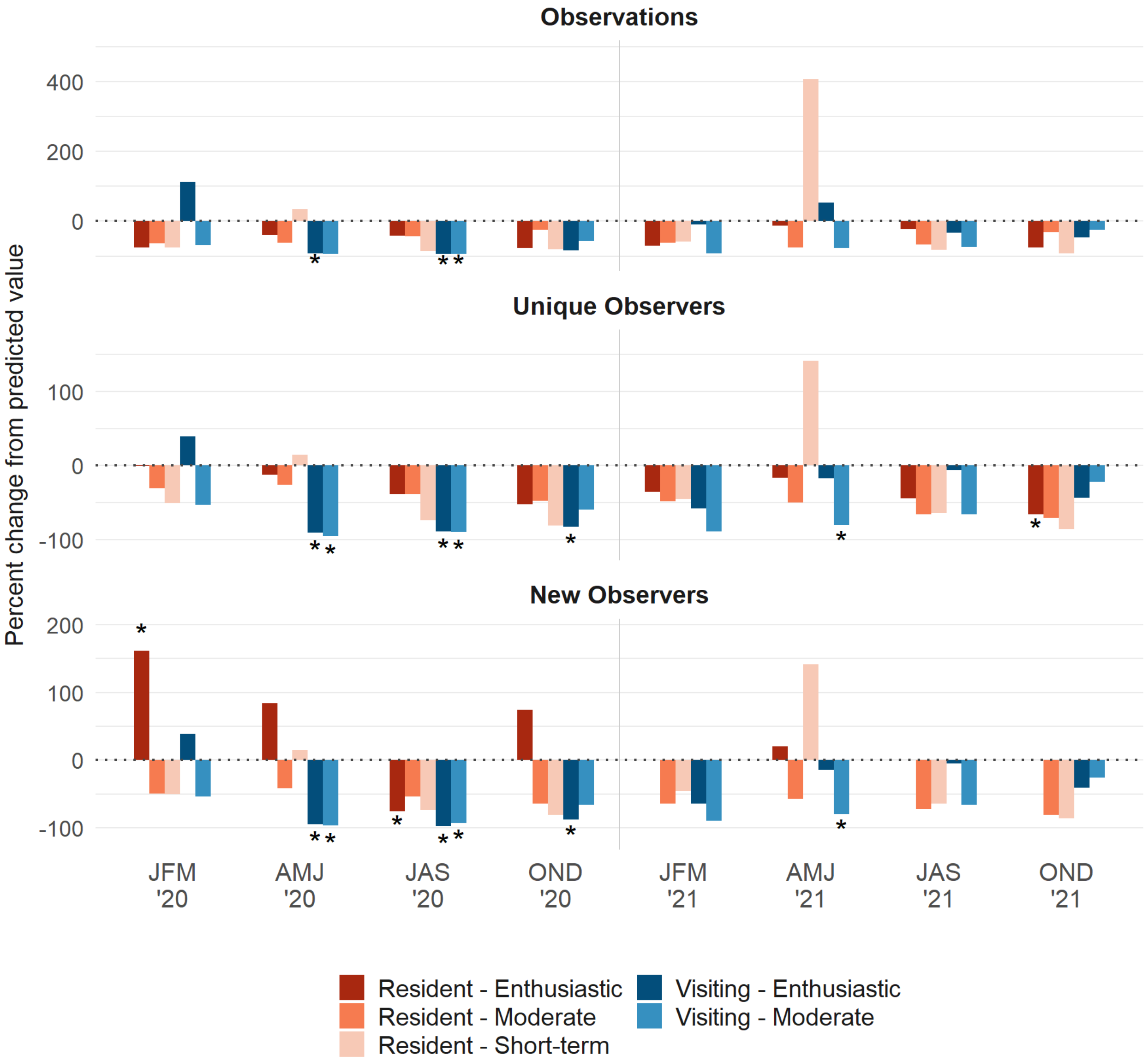


Figure 2.5
Difference between the number of observed and predicted observations, unique observers, and new observers in 2020-2021, calculated by observer behavior. Significant differences (*) determined using 95% confidence interval. Visiting short-term group excluded due to low number of samples.

In 2021, total observations lower than expected based on 2008-2019 linear models, albeit statistically non-significant (Appendix A, Table A3). The number of unique observers was also lower than expected, except during JAS (Appendix A, Table A4). Results were more variable within quarters and observer, observation quality, taxonomic, and spatial classes. Fishes and amphibians were the only taxonomic groups that exceeded expected values for 2021. Wetland observations were significantly lower than expected in JFM. In AMJ, resident-short-term participation greatly exceeded expected values, while unique and new moderate visitors were significantly lower than expected (Figure 2.5). When calculated over the entire year, visiting-enthusiastic participation metrics were closest to expected values, followed by those of the visiting-moderate group.

All metrics surpassed 2019 values in 2021: observations increased by 85.9%, unique observers by 56.9%, and new observers by 54.1%. Growth in unique observers was highest for casual observations (Appendix A, Figure A4). Among taxonomic groups, fishes had the highest increase in both observations and unique observers compared to 2019 (Appendix A, Figure A4). Spatial bias did not statistically differ from previous years, though 2021 growth in observations was relatively higher in wet forest/shrub, lands managed for multiple uses, and sites up to 1,513 meters from a road or trail (Appendix A, Figures A4). Growth in unique observers was highest in wetland/water and bare ground land cover types, and areas with limited protections. For observers, the highest growth in participation often occurred among resident-short-term observers (Appendix A, Figure A5). Resident-enthusiastic observers also experienced high growth in observations, while unique observers increased in both moderate groups.

2.4. Discussion

2.4.1. Bias toward highly impacted landscapes

iNaturalist observations in Hawaii were skewed toward sites with a higher human impact (i.e. areas that are developed, closer to roads or trails, and have fewer protections). This is a common bias in citizen science projects, including the global iNaturalist dataset (Di Cecco et al., 2021; Fletcher et al., 2019; Mair & Ruete, 2016). Though the magnitude of bias varied somewhat from year to year, more accessible, developed sites have been consistently overrepresented since the app's launch in 2008 and throughout the COVID-19 pandemic.

Annual land designation trends were more variable, but observations over the full study period were biased toward non-designated sites and those with limited protections. Previous studies indicate that citizen science bias toward protected areas varies regionally, and may be influenced by site characteristics of the protected areas themselves (Johnston et al., 2020; Tang et al., 2021; Tulloch et al., 2013). In separating designated lands by GAP status, we found that protected areas more explicitly managed for biodiversity were undersampled in Hawaii, while those that permit intensive anthropogenic use and disturbance were sampled more intensely.

If observers are primarily active in more 'convenient' or accessible locations, they may be more likely to record common, easily-detected species (Callaghan et al., 2020; Di Cecco et al., 2021). For example, an increase in urban observations during COVID-19 lockdowns in Colombia coincided with fewer reports of threatened and endemic species (Sánchez-Clavijo et al., 2021). An exceptionally high proportion of native Hawaiian species are endemic and prone to endangerment due to their relatively narrow ranges and low population densities (Pratt, 2009; Sakai et al., 2002). Our land cover analysis suggests that iNaturalist data may have limited capacity to capture rare or at-risk taxa (Lloyd et al., 2020), particularly in native wetlands and wet and dry forests, which were sampled much less than developed areas despite being some of the islands' most diverse ecosystems with high rates of endemism (Javar-Salas et al., 2020; Sakai et al., 2002). Though wetlands were overrepresented relative to their area, well-sampled sites were largely concentrated in coastal areas near roads and trails, rather than in high-elevation native bogs.

The skew toward human-impacted sites could potentially be influenced by the high number of non-native species in Hawaii, which have significantly altered native patterns of diversity (Craven et al., 2019; Cuddihy & Stone, 1990). Concentrations of invasive and non-native species would not be unexpected on disturbed road- and trail-sides or in developed and less-protected areas. A species-level analysis would be needed to distinguish the effects of true non-native species occurrence versus observer bias. However, land-use change, habitat fragmentation, and species invasions are more often associated with a loss in species richness (Flaspohler et al., 2010; Martínez-Ramos et al., 2016; Murphy & Romanuk, 2014), and the relatively low abundance of observations in Hawaii's most diverse habitats indicates at least some degree of observer bias.

While spatial bias limits the inferences that can be made about species distributions or population changes (Kamp et al., 2016), particularly in more remote locations, the observations are not without utility. Many statistical approaches can be employed to address sampling bias (Fletcher et al., 2019; Steen et al., 2021; Varela et al., 2014), and spatially biased observations may be less problematic when used to complement professional, structured data in low-priority habitats (Martin et al., 2012) or areas that have not been surveyed yet or as extensively (Lehtiniemi et al., 2020; Robinson et al., 2020). Observations can also be filtered by quality; the Global Biodiversity Information Facility (www.gbif.org) and many papers have exclusively used research-grade iNaturalist data (e.g. Crimmins et al., 2021; Jacobs & Zipf, 2017; Pearman-Gillman et al., 2020; Smith & Nimbs, 2022), which show less spatial bias toward human-impacted areas than casual observations. Finally, monitoring in human-impacted landscapes has value in and of itself. Citizen science in urban areas provides long-term data collection on the response of biodiversity to urbanization (Callaghan et al., 2018, 2019; Hawthorne et al., 2015), and gives participants the opportunity to connect with local natural history and contribute to biodiversity research with local implications (Ballard et al., 2017).

2.4.2. Preference vs. accessibility

It is difficult to determine the degree to which sampling bias is driven by observer preference or site accessibility (Leonard, 2008; Tulloch & Szabo, 2012), but spatial patterns during the COVID-19 lockdown may offer some insight in Hawaii. Though spatial biases in 2020-2021 did not differ significantly from previous years, certain trends were amplified in the quarters immediately after the onset of the pandemic. Participation decreased in dry/mesic forest, bare ground sites, and areas managed for biodiversity, while developed and non-designated areas saw a relative increase in activity. Shelter-in-place mandates (Office of the Governor, 2020b), coupled with spring and summer closures of state parks and beaches (Division of State Parks, 2020; HNN Staff, 2020), suggest that this spatial shift was largely driven by access. Previous studies have noted that urban activity increased in regions where COVID-19 lockdowns restricted movement and park access (Basile et al., 2021; Crimmins et al., 2021; Sánchez-Clavijo et al., 2021), while urban and non-urban observations were similar in regions where residents were less confined to cities (Sweet et al., 2022).

In 2021, participation rebounded more strongly in underrepresented sites (e.g. wet forest/shrub, protected and more intensely managed lands, sites further from roads and trails), a possible indication of observer interest in these sites once barriers to access were lifted. Whether this trend will persist into the future is uncertain. Additionally, sampling bias toward developed and non-designated areas differs among observer behavior groups. Bias toward human-impacted sites was relatively lower for enthusiastic observers prior to the pandemic, and did not increase in

2020. Future research could explore whether this difference among participants is due to preference for or unequal access to more “natural” sites.

2.4.3. Data quality implications of observer trends

Nearly half of the iNaturalist observations in Hawaii have been contributed by very active, enthusiastic observers who represent a minority of participants. Short-term observers outnumbered enthusiastic observers, and sampling patterns between them differed beyond sheer volume. Observations made by short-term and moderate observers showed higher spatial bias and were less likely to include the attributes required to become research-grade. These data are more difficult to use, as species identifications cannot be verified and true spatial patterns may be obscured. Perhaps unsurprisingly, enthusiastic observers were the most likely to make research-grade observations; as the participants who have invested the most time on the app, they might also be expected to document more observation attributes. We also found greater taxonomic and spatial diversity in sampling by enthusiastic observers, who were more likely to visit sites outside of highly impacted, overrepresented areas. In essence, the breadth, as well as the bulk, of iNaturalist sampling was carried out by a small percentage of observers.

While a small percentage of highly active users has been observed in other citizen science datasets (Boakes et al., 2016; Larson et al., 2020), we also found that the majority of Hawaii’s most active iNaturalist observers were unlikely to live in the state. Visitors represented nearly two-thirds of observers in this study and the majority of enthusiastic (95.9%) and moderate (73.6%) observers. This may be expected given that Hawaii’s relatively small population has been consistently outnumbered by tourists for several decades (Trask, 1992), and observers who elect to participate while traveling are likely to be more experienced or active on the app in general (Hobbs & White, 2012). Investigating citizen science participation in other regions with significant tourism sectors may reveal similar trends.

Meanwhile, short-term resident observers represented nearly half of all residents and were exhibiting the highest growth in participation prior to 2020. These briefly-active participants may have initially encountered iNaturalist by chance or through short-term events like bioblitzes, which can be hosted through iNaturalist projects and are effective at drawing in new, albeit episodic or one-time, participants (Ballard et al., 2017; Rochester, 2006; Rotman et al., 2014). Spikes in new short-term observers in 2015-2016 coincided with the launch of new iNaturalist projects by the Bishop Museum (Hawaii Biological Survey, 2018) and Hawaiʻi Volcanoes National Park (Ferracane, 2015).

A high proportion of one-time participants is not uncommon in citizen science projects of this scale and structure (Boakes et al., 2016; Di Cecco et al., 2021), but the differences between short-term and enthusiastic observers accordingly apply to residents and visitors. Resident-short-term observers were the least likely to sample outside of highly human-impacted sites, suggesting a disparity in site access between residents and visitors. Residents were also more likely to make casual observations. This could also result in resident-collected data representing an even smaller percentage of the iNaturalist data used in research (Di Cecco et al., 2021). Improved retention and engagement of locally-based participants is needed to address these potential gaps, and could have benefits for biodiversity monitoring as well. We found that resident-enthusiastic observers, though few in number, were the group most likely to record multiple taxonomic groups and sample a diversity of site types.

In order to expand the scope of monitoring via low-structure but accessible platforms, it is important to consider how to retain and encourage existing participants (Boakes et al., 2016;

Maund et al., 2020). To be clear, citizen science participation yields benefits beyond data collection for researchers, and all engagement is valuable (Bonney et al., 2016; Coventry et al., 2019). In the context of biodiversity monitoring, however, long-term participation is particularly useful for understanding changes in species populations dynamics. Though iNaturalist has been extremely successful in attracting new users (iNaturalist, 2022a), the majority are inactive and participate very infrequently; many have submitted just one observation (Di Cecco et al., 2021). Even if overall engagement on a platform is consistently growing, high-quality, representative datasets may be more difficult to assemble if participation by individual observers is sporadic (Kamp et al., 2016; McKinley et al., 2017). Encouraging sustained, local participation may thus help to improve the quality, utility, as well as stability of iNaturalist data collection.

2.4.4. Impact of COVID-19 on residents and visitors

The COVID-19 pandemic made evident one consequence of the high proportion of visiting iNaturalist observers. Though participation in all observer groups was lower than expected in 2020, the drop in visiting-moderate and visiting-enthusiastic observer activity was significant throughout much of the year. Thus, total iNaturalist observations decreased, in spite of relatively steady participation among residents. While resident-moderate observers were generally the most active, the number of resident-short-term observers and observations were greater than expected during AMJ 2020. Shelter-in-place orders during this time may have motivated new participants to sign up for the app (Sanderfoot et al., 2022). If so, the effect was short-lived and the new observers were only briefly active.

Quarantine restrictions were relaxed and COVID-19 testing became more widely available toward the end of 2020. By JFM 2021, participation among observer groups began to rise (Figure 2.4). However, it was still lower than expected, particularly for resident observers.

Resident-short-term observers experienced another AMJ spike (Figure 2.5), which may be related to several bioblitzes that take place during the spring (e.g. City Nature Challenge, Hawaiʻi Intertidal Bioblitz). Despite this gain, the enthusiastic and moderate visitors were the closest to achieving expected rates of participation in 2021. Continued study could clarify whether COVID-19 had temporary or lasting effects on resident versus visitor activity in Hawaii.

COVID-19 lockdowns disrupted long-term professional data collection by halting field research and travel (Corlett et al., 2020). In some regions, monitoring via citizen science increased (Sweet et al., 2022) or was less affected than professional surveying (Stenhouse et al., 2022). In Hawaii, iNaturalists still collected thousands of observations in 2020. But the greatest declines in observations (from 2019) occurred for enthusiastic and visiting observers. This coincided with greater relative decreases in research-grade-eligible observations, and, as previously discussed, increased sampling of human-impacted sites. If collection of spatially diverse, high-quality observations primarily depends on the mobility of a small group of participants, then broad-scale citizen science via programs like iNaturalist appears vulnerable to the same events that disrupt professional research.

2.4.5. Other considerations

Long-term participation is often motivated by trust, mentorship, and relationships between participants and professional scientists, or participants and their communities (Rotman et al., 2014). Though iNaturalist can certainly be used to support these interactions, the app can also be easily used in solitude, and many biodiversity citizen science projects are shifting toward this independent format that may put more distance between researchers and volunteers (Maund et al., 2020). On their own, such projects may be insufficiently engaging for new participants without pre-existing interests or personal motivations. Opportunities for feedback, learning, training, and collaboration with researchers are needed as well, and could be provided through institutions (e.g. museums) that can work with community-based groups to foster a more collective and inclusive experience (Ballard et al., 2017; Chesser et al., 2020; Pandya, 2012). These efforts are especially important for ensuring that audiences who have been historically underrepresented in or excluded from citizen science are able to participate in biodiversity conservation.

Our results demonstrated that an active, local participant base is invaluable for consistent data collection, particularly during extraordinary circumstances like the COVID-19 pandemic. In order to ask relevant questions and produce relevant outcomes, citizen science projects must aim to increase inclusivity and prioritize local participation and perspectives (Cooper et al., 2021; Pocock et al., 2018). Our study can infer little about iNaturalist demographics in Hawaii, but there is a clear imbalance between residents and visitors who have the means to travel, perhaps regularly, to this isolated region. An in-depth investigation of citizen science participants—in iNaturalist or one of the many other projects in Hawaii (Grossman, 2022; Sherwood, 2020)—would be needed to identify specific ethnic or socioeconomic disparities. However, citizen science participants are rarely representative of the general population, and instead tend to be white, male, and older, with higher levels of income and/or education (Hobbs & White, 2012; Larson et al., 2020; Maund et al., 2020; Pateman et al., 2021; Trumbull et al., 2000; West et al., 2016), i.e. the demographics that have traditionally dominated professional science (Soleri et al., 2016). This may intensify the disconnect between researchers and the communities in which they operate, particularly since many citizen science projects (like iNaturalist) are supported by academic institutions, government agencies, or other professional organizations (Rotman et al., 2014), and thus do not challenge existing power dynamics between these formal centers of expertise and the volunteers who are critical to sustaining data collection (Pocock et al., 2018). Important recommendations for engaging a more diverse citizen science community have been made elsewhere, but it is important to also acknowledge that many barriers to participation for marginalized groups are symptoms of larger socioeconomic disparities (Pandya, 2012).

2.5. Conclusions

Our analysis of iNaturalist participation in Hawaii corroborated some of the general patterns described in previous studies: sampling grew exponentially until 2020, decreased during COVID-19 lockdowns, and rebounded in 2021. Spatial biases toward human-impacted landscapes have remained relatively constant over time and increased somewhat during the early stages of the pandemic. A small percentage of observers contributed a large proportion of observations. However, we also found that that these trends varied by observer behavior, and that iNaturalist biodiversity monitoring in Hawaii was primarily driven by highly active visitors. Visitors were generally more active and greater in number. Residents were the minority of iNaturalists in Hawaii, and because many were short-term participants, their observations tended to be casual and more biased toward human-impacted landscapes. Yet enthusiastic residents, while small in number, made the most spatially and taxonomically diverse observations. The COVID-19 pandemic further demonstrated the particular importance of local participation, for though visitor activity decreased sharply at the onset of travel restrictions, participation by residents remained relatively steady, and several spikes in new resident observers occurred. By 2021, however, visiting observers were closest to reaching expected rates of participation. In order to achieve more consistent, higher quality biodiversity monitoring via citizen science, it is important to encourage sustained and local participation.

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References

Agrusa, J., Linnes, C., Lema, J., Min, J. (Ellie), Henthorne, T., Itoga, H., & Lee, H. (2021). Tourism Well-Being and Transitioning Island Destinations for Sustainable Development. *Journal of Risk and Financial Management*, *14*(1), 32. doi:10.3390/jrfm14010032

Ballard, H. L., Robinson, L. D., Young, A. N., Pauly, G. B., Higgins, L. M., Johnson, R. F., & Tweddle, J. C. (2017). Contributions to conservation outcomes by natural history museum-led citizen science: Examining evidence and next steps. *Biological Conservation*, *208*, 87–97. doi:10.1016/j.biocon.2016.08.040

Basile, M., Russo, L. F., Russo, V. G., Senese, A., & Bernardo, N. (2021). Birds seen and not seen during the COVID-19 pandemic: The impact of lockdown measures on citizen science bird observations. *Biological Conservation*, *256*, 109079. doi:10.1016/j.biocon.2021.109079

Bates, A. E., Primack, R. B., Moraga, P., & Duarte, C. M. (2020). COVID-19 pandemic and associated lockdown as a “Global Human Confinement Experiment” to investigate biodiversity conservation. *Biological Conservation*, *248*, 108665. doi:10.1016/j.biocon.2020.108665

Boakes, E. H., Gliozzo, G., Seymour, V., Harvey, M., Smith, C., Roy, D. B., & Haklay, M. (2016). Patterns of contribution to citizen science biodiversity projects increase understanding of volunteers’ recording behaviour. *Scientific Reports*, *6*(1), 33051. doi:10.1038/srep33051

Boakes, E. H., McGowan, P. J. K., Fuller, R. A., Chang-qing, D., Clark, N. E., O’Connor, K., & Mace, G. M. (2010). Distorted views of biodiversity: Spatial and temporal bias in species occurrence data. *PLoS Biology*, *8*(6), e1000385. doi:10.1371/journal.pbio.1000385

Bonney, R., Phillips, T. B., Ballard, H. L., & Enck, J. W. (2016). Can citizen science enhance public understanding of science? *Public Understanding of Science*, *25*(1), 2–16. doi:10.1177/0963662515607406

Botts, E. A., Erasmus, B. F. N., & Alexander, G. J. (2011). Geographic sampling bias in the South African Frog Atlas Project: Implications for conservation planning. *Biodiversity and Conservation*, *20*(1), 119–139. doi:10.1007/s10531-010-9950-6

Callaghan, C. T., Major, R. E., Lyons, M. B., Martin, J. M., & Kingsford, R. T. (2018). The effects of local and landscape habitat attributes on bird diversity in urban gre100enspaces. *Ecosphere*, *9*(7), e02347. doi:10.1002/ecs2.2347

Callaghan, C. T., Major, R. E., Lyons, M. B., Martin, J. M., Wilshire, J. H., Kingsford, R. T., & Cornwell, W. K. (2019). Using citizen science data to define and track restoration targets in urban areas. *Journal of Applied Ecology*, 1365-2664.13421. doi:10.1111/1365-2664.13421

Callaghan, C. T., Ozeroff, I., Hitchcock, C., & Chandler, M. (2020). Capitalizing on opportunistic citizen science data to monitor urban biodiversity: A multi-taxa framework. *Biological Conservation*, *251*, 108753. doi:10.1016/j.biocon.2020.108753

Chesser, S., Porter, M. M., & Tuckett, A. G. (2020). Cultivating citizen science for all: Ethical considerations for research projects involving diverse and marginalized populations. *International Journal of Social Research Methodology*, *23*(5), 497–508. doi:10.1080/13645579.2019.1704355

Chun, J., Chun, M.-C., Liu, L., Kwan, A., & Patoskie, J. (2019). *2019 Annual Visitor Research Report* (p. 184). Hawaiʻi Tourism Authority. https://www.hawaiitourismauthority.org/media/5062/2019-annual-report-final-for-posting.pdf

Chun, J., Chun, M.-C., Liu, L., Patoskie, J., Kwan, A., Rockholm, P., & Tadena, N. (2020). *2020 Annual Visitor Research Report* (p. 185). Hawaiʻi Tourism Authority.

Cooper, C. B., Hawn, C. L., Larson, L. R., Parrish, J. K., Bowser, G., Cavalier, D., Dunn, R. R., Haklay, M. (Muki), Gupta, K. K., Jelks, N. O., Johnson, V. A., Katti, M., Leggett, Z., Wilson, O. R., & Wilson, S. (2021). Inclusion in citizen science: The conundrum of rebranding. *Science*, *372*(6549), 1386–1388. doi:10.1126/science.abi6487

Corlett, R. T., Primack, R. B., Devictor, V., Maas, B., Goswami, V. R., Bates, A. E., Koh, L. P., Regan, T. J., Loyola, R., Pakeman, R. J., Cumming, G. S., Pidgeon, A., Johns, D., & Roth, R. (2020). Impacts of the coronavirus pandemic on biodiversity conservation. *Biological Conservation*, *246*, 108571. doi:10.1016/j.biocon.2020.108571

Coventry, P. A., Neale, C., Dyke, A., Pateman, R., & Cinderby, S. (2019). The Mental Health Benefits of Purposeful Activities in Public Green Spaces in Urban and Semi-Urban Neighbourhoods: A Mixed-Methods Pilot and Proof of Concept Study. *International Journal of Environmental Research and Public Health*, *16*(15), 2712. doi:10.3390/ijerph16152712

Craven, D., Knight, T. M., Barton, K. E., Bialic-Murphy, L., & Chase, J. M. (2019). Dissecting macroecological and macroevolutionary patterns of forest biodiversity across the Hawaiian archipelago. *Proceedings of the National Academy of Sciences*, *116*(33), 16436–16441. doi:10.1073/pnas.1901954116

Crimmins, T. M., Posthumus, E., Schaffer, S., & Prudic, K. L. (2021). COVID-19 impacts on participation in large scale biodiversity-themed community science projects in the United States. *Biological Conservation*, *256*, 109017. doi:10.1016/j.biocon.2021.109017

Cuddihy, L. W., & Stone, C. P. (1990). *Alteration of native Hawaiian vegetation: Effects of humans, their activities and introductions*. University of Hawaii, Cooperative National Park Resources Studies Unit. https://pcsuhawaii.org/books-1990/

Dennis, R. L. H., & Thomas, C. D. (2000). Bias in Butterfly Distribution Maps: The Influence of Hot Spots and Recorder's Home Range. *Journal of Insect Conservation*, *4*(2), 73–77. doi:10.1023/A:1009690919835

Di Cecco, G. J., Barve, V., Belitz, M. W., Stucky, B. J., Guralnick, R. P., & Hurlbert, A. H. (2021). Observing the Observers: How Participants Contribute Data to iNaturalist and Implications for Biodiversity Science. *BioScience*, *71*(11), 1179–1188. doi:10.1093/biosci/biab093

Division of State Parks. (2020). *Hawaii State Parks & COVID-19*. Department of Land and Natural Resources. https://dlnr.hawaii.gov/dsp/covid-19-x-hawaii-state-parks/

Farias, M., Roper, J., & Cavarzere, V. (2022). Bird Communities and Their Conservation Priorities are Better Understood through the Integration of Traditional and Citizen Science Data: An Example from Brazilian Atlantic Forest. *Citizen Science: Theory and Practice*, *7*(1), 9. doi:10.5334/cstp.349

Ferracane, J. (2015, April 7). *Hawaiʻi Volcanoes National Park to Host BioBlitz 2015*. National Park Service. https://www.nps.gov/havo/learn/news/20150407_pr_bioblitz.htm

Flaspohler, D. J., Giardina, C. P., Asner, G. P., Hart, P., Price, J., Lyons, C. K., & Castaneda, X. (2010). Long-term effects of fragmentation and fragment properties on bird species richness in Hawaiian forests. *Biological Conservation*, *143*(2), 280–288. doi:10.1016/j.biocon.2009.10.009

Fleischer, R. C., Mcintosh, C. E., & Tarr, C. L. (1998). Evolution on a volcanic conveyor belt: Using phylogeographic reconstructions and K–Ar-based ages of the Hawaiian Islands to estimate molecular evolutionary rates. *Molecular Ecology*, *7*(4), 533–545. doi:10.1046/j.1365-294x.1998.00364.x

Fletcher, R. J., Hefley, T. J., Robertson, E. P., Zuckerberg, B., McCleery, R. A., & Dorazio, R. M. (2019). A practical guide for combining data to model species distributions. *Ecology*, e02710. doi:10.1002/ecy.2710

Freitag, A., Meyer, R., & Whiteman, L. (2016). Strategies Employed by Citizen Science Programs to Increase the Credibility of Their Data. *Citizen Science: Theory and Practice, 1*(1), 2. doi:10.5334/cstp.6

Geldmann, J., Heilmann-Clausen, J., Holm, T. E., Levinsky, I., Markussen, B., Olsen, K., Rahbek, C., & Tøttrup, A. P. (2016). What determines spatial bias in citizen science? Exploring four recording schemes with different proficiency requirements. *Diversity and Distributions*, *22*(11), 1139–1149. doi:10.1111/ddi.12477

Gratzer, K., & Brodschneider, R. (2021). How and why beekeepers participate in the INSIGNIA citizen science honey bee environmental monitoring project. *Environmental Science and Pollution Research*, *28*(28), 37995–38006. doi:10.1007/s11356-021-13379-7

Grossman, D. (2022, April 11). Citizen science: It takes a village. *Maui News*. https://www.mauinews.com/news/local-news/2022/04/citizen-science-it-takes-a-village/

Hawaii Biological Survey. (2018, October 9). Bishop Museum's Hawaii Biological Survey now has a citizen science component. *INaturalist*. https://www.inaturalist.org/projects/hawaii-biological-survey/journal

Hawthorne, T. L., Elmore, V., Strong, A., Bennett-Martin, P., Finnie, J., Parkman, J., Harris, T., Singh, J., Edwards, L., & Reed, J. (2015). Mapping non-native invasive species and accessibility in an urban forest: A case study of participatory mapping and citizen science in Atlanta, Georgia. *Applied Geography*, *56*, 187–198. doi:10.1016/j.apgeog.2014.10.005

HNN Staff. (2020, August 7). As COVID-19 cases surge, parks, beaches to close and inter-island quarantine returns. *Hawaii News Now*. https://www.hawaiinewsnow.com/2020/08/06/live-governor-outline-plan-reining-covid-surge-oahu/

Hobbs, S. J., & White, P. C. L. (2012). Motivations and barriers in relation to community participation in biodiversity recording. *Journal for Nature Conservation*, *20*(6), 364–373. doi:10.1016/j.jnc.2012.08.002

iNaturalist. (2022a). *Site Stats*. https://www.inaturalist.org/stats

iNaturalist. (2022b, January 3). *Year In Review 2021*. iNaturalist. https://www.inaturalist.org/stats/2021

Jacobi, J. D., Price, J. P., Fortini, L. B., M, G. I., Samuel, & Berkowitz, P. (2017). *Hawaii Land Cover and Habitat Status* [Data set]. U.S. Geological Survey. doi:10.5066/F7DB80B9

Jacobs, C., & Zipf, A. (2017). Completeness of citizen science biodiversity data from a volunteered geographic information perspective. *Geo-Spatial Information Science*, *20*(1), 3–13. doi:10.1080/10095020.2017.1288424

Javar-Salas, C. M., Pe‘a, R., Amidon, F., Reeves, M. K., & Miller, S. E. (2020). Hawaiian Islands Dry Forest. In *Encyclopedia of the World's Biomes* (pp. 295–327). Elsevier. doi:10.1016/B978-0-12-409548-9.11890-1

Johnston, A., Hochachka, W. M., Strimas-Mackey, M. E., Ruiz Gutierrez, V., Robinson, O. J., Miller, E. T., Auer, T., Kelling, S. T., & Fink, D. (2021). Analytical guidelines to increase the value of community science data: An example using eBird data to estimate species distributions. *Diversity and Distributions*, *27*(7), 1265–1277. doi:10.1111/ddi.13271

Johnston, A., Moran, N., Musgrove, A., Fink, D., & Baillie, S. R. (2020). Estimating species distributions from spatially biased citizen science data. *Ecological Modelling*, *422*, 108927. doi:10.1016/j.ecolmodel.2019.108927

Kadmon, R., Farber, O., & Danin, A. (2004). Effect of roadside bias on the accuracy of predictive maps produced by bioclimatic models. *Ecological Applications*, *14*(2), 401–413. doi:10.1890/02-5364

Kamp, J., Oppel, S., Heldbjerg, H., Nyegaard, T., & Donald, P. F. (2016). Unstructured citizen science data fail to detect long-term population declines of common birds in Denmark. *Diversity and Distributions*, *22*(10), 1024–1035. doi:10.1111/ddi.12463

Kelling, S., Johnston, A., Bonn, A., Fink, D., Ruiz-Gutierrez, V., Bonney, R., Fernandez, M., Hochachka, W. M., Julliard, R., Kraemer, R., & Guralnick, R. (2019). Using Semistructured Surveys to Improve Citizen Science Data for Monitoring Biodiversity. *BioScience*, *69*(3), 170–179. doi:10.1093/biosci/biz010

Kishimoto, K., & Kobori, H. (2021). COVID-19 pandemic drives changes in participation in citizen science project “City Nature Challenge” in Tokyo. *Biological Conservation*, *255*, 109001. doi:10.1016/j.biocon.2021.109001

Kullenberg, C., & Kasperowski, D. (2016). What Is Citizen Science? – A Scientometric Meta-Analysis. *PLOS ONE*, *11*(1), e0147152. doi:10.1371/journal.pone.0147152

Larson, L. R., Cooper, C. B., Futch, S., Singh, D., Shipley, N. J., Dale, K., LeBaron, G. S., & Takekawa, J. Y. (2020). The diverse motivations of citizen scientists: Does conservation emphasis grow as volunteer participation progresses? *Biological Conservation*, *242*, 108428. doi:10.1016/j.biocon.2020.108428

Lehtiniemi, M., Outinen, O., & Puntila-Dodd, R. (2020). Citizen science provides added value in the monitoring for coastal non-indigenous species. *Journal of Environmental Management*, *267*, 110608. doi:10.1016/j.jenvman.2020.110608

Leonard, D. L. (2008). Recovery expenditures for birds listed under the US Endangered Species Act: The disparity between mainland and Hawaiian taxa. *Biological Conservation*, *141*(8), 2054–2061. doi:10.1016/j.biocon.2008.06.001

Lloyd, T. J., Fuller, R. A., Oliver, J. L., Tulloch, A. I., Barnes, M., & Steven, R. (2020). Estimating the spatial coverage of citizen science for monitoring threatened species. *Global Ecology and Conservation*, *23*, e01048. doi:10.1016/j.gecco.2020.e01048

Mair, L., & Ruete, A. (2016). Explaining Spatial Variation in the Recording Effort of Citizen Science Data across Multiple Taxa. *PLOS ONE*, *11*(1), e0147796. doi:10.1371/journal.pone.0147796

Martin, L. J., Blossey, B., & Ellis, E. (2012). Mapping where ecologists work: Biases in the global distribution of terrestrial ecological observations. *Frontiers in Ecology and the Environment*, *10*(4), 195–201. doi:10.1890/110154

Martínez-Ramos, M., Ortiz-Rodríguez, I. A., Piñero, D., Dirzo, R., & Sarukhán, J. (2016). Anthropogenic disturbances jeopardize biodiversity conservation within tropical rainforest reserves. *Proceedings of the National Academy of Sciences*, *113*(19), 5323–5328. doi:10.1073/pnas.1602893113

Maund, P. R., Irvine, K. N., Lawson, B., Steadman, J., Risely, K., Cunningham, A. A., & Davies, Z. G. (2020). What motivates the masses: Understanding why people contribute to conservation citizen science projects. *Biological Conservation*, *246*, 108587. doi:10.1016/j.biocon.2020.108587

McGoff, E., Dunn, F., Cachazo, L. M., Williams, P., Biggs, J., Nicolet, P., & Ewald, N. C. (2017). Finding clean water habitats in urban landscapes: Professional researcher vs citizen science approaches. *Science of The Total Environment*, *581–582*, 105–116. doi:10.1016/j.scitotenv.2016.11.215

McKinley, D. C., Miller-Rushing, A. J., Ballard, H. L., Bonney, R., Brown, H., Cook-Patton, S. C., Evans, D. M., French, R. A., Parrish, J. K., Phillips, T. B., Ryan, S. F., Shanley, L. A., Shirk, J. L., Stepenuck, K. F., Weltzin, J. F., Wiggins, A., Boyle, O. D., Briggs, R. D., Chapin, S. F., … Soukup, M. A. (2017). Citizen science can improve conservation science, natural resource management, and environmental protection. *Biological Conservation*, *208*, 15–28. doi:10.1016/j.biocon.2016.05.015

Meyer, C., Weigelt, P., & Kreft, H. (2016). Multidimensional biases, gaps and uncertainties in global plant occurrence information. *Ecology Letters*, *19*(8), 992–1006. doi:10.1111/ele.12624

Murphy, G. E. P., & Romanuk, T. N. (2014). A meta-analysis of declines in local species richness from human disturbances. *Ecology and Evolution*, *4*(1), 91–103. doi:10.1002/ece3.909

Myers, N., Mittermeier, R. A., Mittermeier, C. G., da Fonseca, G. A. B., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, *403*(6772), 853–858. doi:10.1038/35002501

Office of the Governor. (2020a, March 17). *Gov. Ige announces state actions to slow the spread of COVID-19*. Governor of the State of Hawaiʻi - David Y. Ige. https://governor.hawaii.gov/newsroom/latest-news/proper-use-of-covid-19-tests-imperative-there-is-a-current-shortage-of-hand-sanitizers-and-toilet-paper-in-hawaii-in-part-because-of-the-publics-over-reaction-to-covid-19-the-hawai/

Office of the Governor. (2020b, May 18). *Governor Ige Outlines Re-Opening, Recovery Plan – Extends 14-Day Quarantine for Travelers To Hawaii, Inter-Island Travelers*. Governor of the State of Hawaiʻi - David Y. Ige. https://governor.hawaii.gov/newsroom/latest-news/office-of-the-governor-news-release-governor-ige-outlines-re-opening-recovery-plan-extends-14-day-quarantine-for-travelers-to-hawaii-inter-island-travelers/

Office of the Governor. (2021, July 24). *Hawaiʻi bound domestic travelers fully vaccinated in U.S., to bypass testing/quarantine starting July 8*. Governor of the State of Hawaiʻi - David Y. Ige. https://governor.hawaii.gov/newsroom/office-of-the-governor-news-release-hawaii-bound-domestic-travelers-fully-vaccinated-in-u-s-to-bypass-testing-quarantine-starting-july-8/

Pandya, R. E. (2012). A framework for engaging diverse communities in citizen science in the US. *Frontiers in Ecology and the Environment*, *10*(6), 314–317. doi:10.1890/120007

Pateman, R., Dyke, A., & West, S. (2021). The Diversity of Participants in Environmental Citizen Science. *Citizen Science: Theory and Practice*, *6*(1), 9. doi:10.5334/cstp.369

Pearman-Gillman, S. B., Katz, J. E., Mickey, R. M., Murdoch, J. D., & Donovan, T. M. (2020). Predicting wildlife distribution patterns in New England USA with expert elicitation techniques. *Global Ecology and Conservation*, *21*, e00853. doi:10.1016/j.gecco.2019.e00853

Pernat, N., Kampen, H., Jeschke, J. M., & Werner, D. (2021). Citizen science versus professional data collection: Comparison of approaches to mosquito monitoring in Germany. *Journal of Applied Ecology*, *58*(2), 214–223. doi:10.1111/1365-2664.13767

Pocock, M. J. O., Chandler, M., Bonney, R., Thornhill, I., Albin, A., August, T., Bachman, S., Brown, P. M. J., Cunha, D. G. F., Grez, A., Jackson, C., Peters, M., Rabarijaon, N. R., Roy, H. E., Zaviezo, T., & Danielsen, F. (2018). A Vision for Global Biodiversity Monitoring With Citizen Science. In *Advances in Ecological Research* (Vol. 59, pp. 169–223). Elsevier. doi:10.1016/bs.aecr.2018.06.003

Ponciano, L., & Brasileiro, F. (2014). Finding Volunteers' Engagement Profiles in Human Computation for Citizen Science Projects. *Human Computation*, *1*(2). doi:10.15346/hc.v1i2.12

Pratt, T. K. (Ed.). (2009). *Conservation biology of Hawaiian forest birds: Implications for island avifauna*. Yale University Press.

Riesch, H., & Potter, C. (2014). Citizen science as seen by scientists: Methodological, epistemological and ethical dimensions. *Public Understanding of Science*, *23*(1), 107–120. doi:10.1177/0963662513497324

Robinson, O. J., Ruiz-Gutierrez, Viviana., Reynolds, M. D., Golet, G. H., Strimas-Mackey, M., & Fink, D. (2020). Integrating citizen science data with expert surveys increases accuracy and spatial extent of species distribution models. *Diversity and Distributions*, *26*(8), 976–986. doi:10.1111/ddi.13068

Rochester, C. (2006). *Making sense of volunteering: A literature review*. Volunteering England on behalf of The Commission on the Future of Volunteering.

Rotman, D., Hammock, J., Preece, J., Hansen, D., Boston, C., Bowser, A., & He, Y. (2014, March 1). Motivations Affecting Initial and Long-Term Participation in Citizen Science Projects in Three Countries. *IConference 2014 Proceedings*. iConference 2014 Proceedings: Breaking Down Walls. Culture - Context - Computing. doi:10.9776/14054

Sakai, A. K., Wagner, W. L., & Mehrhoff, L. A. (2002). Patterns of Endangerment in the Hawaiian Flora. *Systematic Biology*, *51*(2), 276–302.

Sánchez-Clavijo, L. M., Martínez-Callejas, S. J., Acevedo-Charry, O., Diaz-Pulido, A., Gómez-Valencia, B., Ocampo-Peñuela, N., Ocampo, D., Olaya-Rodríguez, M. H., Rey-Velasco, J. C., Soto-Vargas, C., & Ochoa-Quintero, J. M. (2021). Differential reporting of biodiversity in two citizen science platforms during COVID-19 lockdown in Colombia. *Biological Conservation, 256*, 109077. doi:10.1016/j.biocon.2021.109077

Sanderfoot, O. V., Kaufman, J. D., & Gardner, B. (2022). Drivers of avian habitat use and detection of backyard birds in the Pacific Northwest during COVID-19 pandemic lockdowns. *Scientific Reports, 12*(1), 1-11.

Sherwood, L. (2020, July 29). *UH Hilo biologists, marine scientists harness the power of citizen science*. UH Hilo Stories. https://hilo.hawaii.edu/chancellor/stories/2020/07/29/citizen-science-in-hawaii/

Smith, S. D. A., & Nimbs, M. J. (2022). Citizen Scientists Record Significant Range Extensions for Tropical Sea Slug Species in Subtropical Eastern Australia. *Diversity*, *14*(4), 244. doi:10.3390/d14040244

Soleri, D., Long, J. W., Ramirez-Andreotta, M. D., Eitemiller, R., & Pandya, R. (2016). Finding Pathways to More Equitable and Meaningful Public-Scientist Partnerships. *Citizen Science: Theory and Practice*, *1*(1), 9. doi:10.5334/cstp.46

Steen, V. A., Elphick, C. S., & Tingley, M. W. (2019). An evaluation of stringent filtering to improve species distribution models from citizen science data. *Diversity and Distributions*, *25*(12), 1857–1869. doi:10.1111/ddi.12985

Steen, V. A., Tingley, M. W., Paton, P. W. C., & Elphick, C. S. (2021). Spatial thinning and class balancing: Key choices lead to variation in the performance of species distribution models with citizen science data. *Methods in Ecology and Evolution*, *12*(2), 216–226. doi:10.1111/2041-210X.13525

Stenhouse, A., Perry, T., Grützner, F., Rismiller, P., Koh, L. P., & Lewis, M. (2022). COVID restrictions impact wildlife monitoring in Australia. *Biological Conservation*, *267*, 109470. doi:10.1016/j.biocon.2022.109470

Struyf, A., Hubert, M., & Rousseeuw, P. (1996). Clustering in an Object-Oriented Environment. *Journal of Statistical Software*, *1*(4). doi:10.18637/jss.v001.i04

Sweet, F. S. T., Rödl, T., & Weisser, W. W. (2022). COVID-19 lockdown measures impacted citizen science hedgehog observation numbers in Bavaria, Germany. *Ecology and Evolution, 12*(6). doi:10.1002/ece3.8989

Tang, B., Clark, J. S., & Gelfand, A. E. (2021). Modeling spatially biased citizen science effort through the eBird database. *Environmental and Ecological Statistics*, *28*(3), 609–630. doi:10.1007/s10651-021-00508-1

Theobald, E. J., Ettinger, A. K., Burgess, H. K., DeBey, L. B., Schmidt, N. R., Froehlich, H. E., Wagner, C., HilleRisLambers, J., Tewksbury, J., Harsch, M. A., & Parrish, J. K. (2015). Global change and local solutions: Tapping the unrealized potential of citizen science for biodiversity research. *Biological Conservation*, *181*, 236–244. doi:10.1016/j.biocon.2014.10.021

Trask, H.-K. (1992). Lovely Hula Lands: Corporate Tourism and the Prostitution of Hawaiian Culture. *Border/Lines*, *Winter 1991/1992*(23), 22–29.

Trumbull, D. J., Bonney, R., Bascom, D., & Cabral, A. (2000). Thinking scientifically during participation in a citizen-science project. *Science Education*, *84*(2), 265–275. doi:10.1002/(SICI)1098-237X(200003)84:2<265::AID-SCE7>3.0.CO;2-5

Tulloch, A. I. T., Mustin, K., Possingham, H. P., Szabo, J. K., & Wilson, K. A. (2013). To boldly go where no volunteer has gone before: Predicting volunteer activity to prioritize surveys at the landscape scale. *Diversity and Distributions*, *19*(4), 465–480. doi:10.1111/j.1472-4642.2012.00947.x

Tulloch, A. I. T., & Szabo, J. K. (2012). A behavioural ecology approach to understand volunteer surveying for citizen science datasets. *Emu - Austral Ornithology*, *112*(4), 313–325. doi:10.1071/MU12009

U.S. Geological Survey Gap Analysis Project. (2018). *Protected Areas Database of the United States (PAD-US): U.S. Geological Survey data release*. U.S. Geological Survey. doi:10.5066/P955KPLE

van Strien, A. J., van Swaay, C. A. M., & Termaat, T. (2013). Opportunistic citizen science data of animal species produce reliable estimates of distribution trends if analysed with occupancy models. *Journal of Applied Ecology*, *50*(6), 1450–1458. doi:10.1111/1365-2664.12158

Vann-Sander, S., Clifton, J., & Harvey, E. (2016). Can citizen science work? Perceptions of the role and utility of citizen science in a marine policy and management context. *Marine Policy*, *72*, 82–93. doi:10.1016/j.marpol.2016.06.026

Varela, S., Anderson, R. P., García-Valdés, R., & Fernández-González, F. (2014). Environmental filters reduce the effects of sampling bias and improve predictions of ecological niche models. *Ecography*. doi:10.1111/j.1600-0587.2013.00441.x

Walden-Schreiner, C., Leung, Y.-F., & Tateosian, L. (2018). Digital footprints: Incorporating crowdsourced geographic information for protected area management. *Applied Geography*, *90*, 44–54. doi:10.1016/j.apgeog.2017.11.004

West, S., Pateman, R., & Dyke, A. (2016). *Motivations and data submissions in citizen science. Report to DEFRA*. Stockholm Environment Institute, University of York.

Chapter 3. Citizen science enhances invasive plant monitoring and estimates of habitat

A version of this chapter has been submitted to *Diversity and Distributions* as Dimson, M., Fortini, L. B., Tingley, M. W., and Gillespie, T.W. Citizen science and professional surveys offer complementary data for understanding invasive plant distributions. *Diversity and Distributions* (*in review*). Supplementary materials for this chapter are provided in Appendix B.

Abstract

Aim: Citizen science offers a cost-effective means of acquiring non-native species data. However, data quality issues due to unstructured sampling approaches may discourage the use of citizen science data by conservationists and professional scientists. To evaluate the utility of low-structure iNaturalist data in non-native species monitoring, we examined vascular plant data for environmental sampling bias and bias toward native versus non-native species. Using four example invasive species, we then compared sampling bias in iNaturalist and professional agency observations and used the data to estimate suitable habitat for each species.

Location: Hawaii, USA

Methods: To assess observer preference for native versus non-native plants, we compared the number of species and observations recorded in iNaturalist to the total number of known species in Hawaii. We quantified environmental sampling biases with respect to site accessibility, status, and disturbance using a bias index. Habitat suitability for four invasive species was modeled in Maxent, using observations from iNaturalist, from agencies, from both sources, and iNaturalist observations that had been spatially and environmentally stratified.

Results: iNaturalist plant observations were biased toward invasive species, which were frequently recorded in areas with greater road/trail density and vegetation disturbance. For the example species, professional agencies tended to sample less accessible and native-dominated sites. Invasive plant models often produced distinct projections with iNaturalist versus agency data, particularly when predicting habitat in disturbed versus native vegetation-dominated sites. Stratifying the iNaturalist data had little impact on how suitable habitat was distributed for the example species.

Main conclusions: Invasive species represented a high proportion of iNaturalist plant observations in Hawaii. Citizen science data from iNaturalist has the potential to complement professional invasive plant monitoring and expand estimates of habitat suitability. Each dataset captured unique environmental conditions, and combined models using both datasets provided a more comprehensive estimate of the species distribution.

3.1. Introduction

A major challenge in conservation biogeography is the collection of high-quality, comprehensive species occurrence data (Richardson & Whittaker, 2010). Monitoring data are essential to early detection, risk analysis, and effective management of non-native species, especially environmentally or economically harmful invasive species (Reaser et al., 2020). However, systematic surveys by trained experts are typically resource-intensive and limited in geographic scale (Hochachka et al., 2012), restricting the utility of the data in broad-scale applications, such as estimating species distributions (Meyer et al., 2016). Non-native species in particular have been historically neglected in biodiversity monitoring, and the databases that do exist remain difficult to access, share, and integrate (Reaser et al., 2020; Wallace et al., 2020).

Biodiversity citizen science, in which volunteers participate in species data collection, offers a cost-effective means of addressing data limitations, as the observations are often greater in spatial and temporal extent as well as more readily accessible (McKinley et al., 2017; Theobald et al., 2015). The availability and relative accessibility of citizen science data has great potential to expand existing information systems for non-native species (Johnson et al., 2020).

Citizen science programs differ in scale and structure in order to balance participant recruitment and experience with data credibility (Freitag et al., 2016). This can result in varying levels of identification accuracy as well as geographic and taxonomic completeness, particularly when observations are collected on an incidental basis (Dickinson et al., 2010). Nonrandom variation in observer ability, preferences, or search effort can produce sampling bias in the observations due to the mismatch between participants' sampling patterns and actual species richness or abundance across space (van Strien et al., 2013). Sampling effort by citizen scientists, for example, is likely to be motivated by accessibility (i.e. roads or other human infrastructure) or interest in species and areas of conservation concern (Botts et al., 2011; Steger et al., 2017; Stolar & Nielsen, 2015; Tulloch et al., 2013). Thus, it is often assumed that there is a trade-off between the quality and quantity of citizen science data (Robinson et al., 2020).

However, sampling biases are not unique to citizen science. Sampling by both professional and citizen scientists is taxonomically biased toward vertebrate species (Theobald et al., 2015). Herbarium data exhibit biases toward roadsides and more accessible, lower elevation areas, as well as seasonal bias toward spring and summer (Daru et al., 2018). In scientific literature, distribution data for ground-feeding birds are biased toward threatened species and protected areas (Boakes et al., 2010). The biases in different datasets can be complementary, and when combined with professional data, citizen science has increased the spatial coverage of monitoring efforts for shorebirds (Robinson et al., 2020), insects (Hochmair et al., 2020; Wilson et al., 2020; Zapponi et al., 2017), large mammals (Farhadinia et al., 2018), and easily recognizable non-native aquatic species (Lehtiniemi et al., 2020). Following brief training, citizen scientists have produced similar field estimates of species cover and occurrence as professional scientists (Crall et al., 2011; Danielsen et al., 2014). Crall et al. (2015) demonstrated that citizen science can expand invasive plant monitoring in Wisconsin and lead to more realistic estimates of habitat through local and regional programs that involve identification training or collaboration with botanists. Nevertheless, the vast majority of citizen science plant data are incidental observations from low-structure programs (Di Cecco et al., 2021). Evaluation of the differences between low-structure citizen science data and professional plant surveys is needed to address assumed disparities in quality, which may otherwise limit the use of citizen science observations in conservation and scientific applications, such as habitat suitability modeling (Lewandowski & Specht, 2015; Riesch & Potter, 2014; Theobald et al., 2015).

Habitat suitability models (HSMs) use the relationship between species occurrence records and the environmental conditions at those locations to predict the species’ potential distribution across sampled and un-sampled space. In invasive species management, HSMs have several applications, including predicting potential spread, disease risk, or range shifts under climate change (Guisan & Thuiller, 2005; Newbold, 2010; Srivastava et al., 2019). Model predictions can be used to identify areas vulnerable to invasion and to guide survey and monitoring efforts that are critical to early detection (Guisan et al., 2013). Though the use of citizen science observations in habitat suitability modeling has increased steadily over the last decade, plant data specifically is currently under-used (Feldman et al., 2021).

The quality of model training and evaluation data is critical to the accuracy of the predictions, and, ideally, species records should be representative of the entire modeled environment (Kramer-Schadt et al., 2013). Predictions based on biased data are often fitted to survey effort rather than the true potential distribution of suitable habitat (Phillips et al., 2009) and may inaccurately estimate species ranges (Beck et al., 2014; Björklund et al., 2016). Sampling bias can be addressed using data filtering treatments (e.g. spatial thinning or subsampling of records, culling by survey effort or observer expertise, or balancing presence and absence data) which can produce more accurate models that match the performance of those based on more structured survey data, though treatments typically do not have a consistent effect across the species modeled (Robinson et al., 2018; Steen et al., 2019, 2021) and will not address a complete lack of occurrence data in a region. Additionally, studies comparing filtered eBird observations to professional data have demonstrated that each dataset contributes unique biases and environmental conditions (Coxen et al., 2017; Robinson et al., 2020; Tanner et al., 2020). Modeling approaches that combine multiple datasets have thus become increasingly common; these range from data pooling to more formal integration techniques that can account for sampling issues (Fletcher et al., 2019).

This research focused on the Hawaiian Islands, a biodiversity hotspot with both exceptionally high levels of endemism and ongoing habitat loss (Myers et al., 2000). Native plant species have become outnumbered by non-native species, some of which are highly invasive and pose significant threats to native ecosystems (Cuddihy & Stone, 1990). Native Hawaiian plants, having evolved in isolation, without herbivores, and largely without broad-scale disturbances like wildfire, are highly vulnerable to habitat loss to and competition with invasive species (Carlquist, 1974; Gillespie et al., 2008; Richardson & Pyšek, 2006). The study has two primary components: a citizen science sampling bias analysis of all vascular plant observations in Hawaii to provide context for non-native species observations, and a species-specific comparison of citizen and professional science data for four example invasive species. Citizen science data were acquired from the global, multi-taxa citizen science platform iNaturalist (www.iNaturalist.org), which we selected for its potential to support monitoring of a diversity of regions and taxonomic groups.

We aimed to address three main questions. First, how do sampling biases in iNaturalist observations of native versus non-native plant species differ in Hawaii? Given that previous studies have found citizen science bias toward rare or threatened species (Matteson et al., 2012; Tulloch et al., 2013), we investigated whether non-native species are well-represented in Hawaii's iNaturalist plant data, then compared environmental sampling bias (with respect to site accessibility, status, and disturbance) in native versus non-native plant observations. Second, how do environmental sampling biases in iNaturalist compare to patterns in professional surveys of invasive plant species? We selected four species that were well-sampled by both iNaturalist citizen scientists and professional regional agencies for this comparison. Third, how do data source, sampling biases, and data filtering treatments influence HSM predictions for the selected study species? We examined relationships between single-source models (i.e. iNaturalist- versus agency-based HSMs); single-source models and combined models (i.e. an HSM using data from both sources); and unfiltered and filtered iNaturalist models.

3.2. Methods

3.2.1. Species data

iNaturalist has a flexible, low-commitment structure with a participant base of over 4 million observers worldwide. Over 200,000 iNaturalist observations have been recorded in

Hawaii since the project launched in 2008. We acquired iNaturalist research-grade observations for vascular plant species on the four largest Hawaiian Islands (Hawai‘i, Maui, O‘ahu, and Kaua‘i) through the Global Biodiversity Information Facility (GBIF.org, 2020). Research-grade observations are dated, georeferenced, and photographed sightings of non-captive organisms whose identification is agreed upon by at least two-thirds of the iNaturalist community. Kaho‘olawe, Lāna‘i, Moloka‘i, and Ni‘ihau were excluded from this analysis due to restricted access to and limited data on the islands (less than 0.7% of iNaturalist plant records occurred on these four islands).

There are a number of regional agencies that work to control and prevent establishment of invasive species in Hawaii. We used invasive plant observations shared by the Big Island Invasive Species Committee, Consortium of Pacific Herbarium, Kaua‘i Invasive Species Committee, Ko‘olau Mountains Watershed Partnership, O‘ahu Army Natural Resource Program, O‘ahu Invasive Species Committee, and Pacific Island Ecosystems Research Center. To compare iNaturalist and agency observations, we selected invasive species with relatively large sample sizes (>100 observations) in both datasets. Four species met this threshold (Fig. 3.1; for overlap in environmental space, see Appendix B, Figure B1). They included long-established species that are close to reaching equilibrium in their Hawaiian range (Vorsino et al., 2014): *Hedychium gardnerianum* Sheph. ex Ker Gawl. [established 1940], an understory species common in rainforests between 0-1,700 m (Minden et al., 2010); *Psidium cattleianum* Sabine [est. 1825], a tree found primarily in rainforests between 150-1,300 m (Smith, 1985); and the shrubs *Lantana camara* L. [est. 1858] and *Leucaena leucocephala* (Lam.) de Wit [est. 1837], which colonize disturbed, dry and mesic lowland habitats up to 1,000 m and 700 m, respectively (Smith, 1985; Wagner et al., 1999).

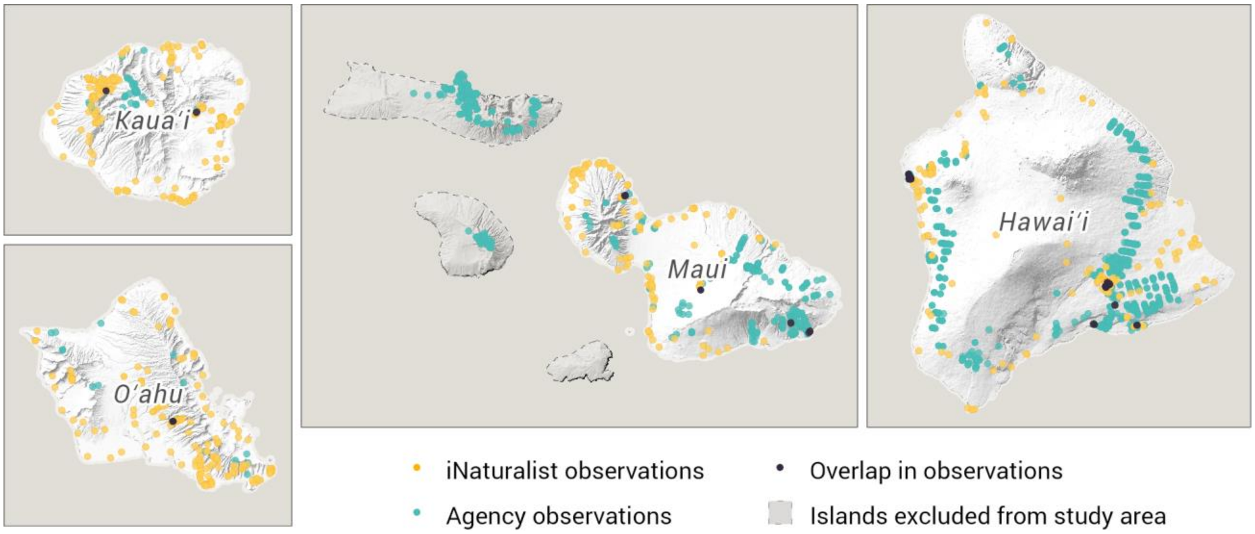

Figure 3.1
Distribution of iNaturalist and professional agency observations for *Hedychium gardnerianum, Lantana camara, Leucaena leucocephala,* and *Psidium cattleianum.*

3.2.2. Sampling bias

In order to evaluate the potential of iNaturalist as a source of invasive species observations, we compared the establishment means—i.e. the process by which a species came to occur in Hawaii (Groom et al., 2019)—of all vascular plants observed in iNaturalist to the species composition of Hawaii overall. Species were divided into three native and three non-native classes (Table 3.1). Endemic, indigenous, and naturalized species occurring on Hawaii's four largest islands were identified from vascular plant checklists (Imada, 2012, 2019). As there is currently no regulatory list of invasive species in Hawaii, invasive and potentially invasive species lists were compiled using the Hawaii-Pacific Weed Risk Assessment (Daehler et al., 2004) and Hawaii's Most Invasive Horticultural Plants list (Hawaii State Alien Species Coordinator, 2017).

We investigated three environmental biases that are likely to influence citizen science sampling, including accessibility bias (clustering near roads and trails), status bias (preference for sites in or near areas of conservation interest), and disturbance bias (disproportionate sampling in more heavily disturbed sites and vegetation communities, where there are likely to be more opportunities for recreation). Accessibility was defined by road and trail density (kilometers per square kilometer), calculated using 2019 TIGER/Line Shapefiles for all roads (prepared by the U.S. Census Bureau 2019) and the Na Ala Hele Trail system (State Department of Land and Natural Resources, DOFAW, updated 2018). Status bias was derived from distance to open and restricted access areas in the U.S. Geological Survey Protected Areas Database (USGS GAP, 2018), an inventory of lands set aside for the preservation of biodiversity, recreation, resource extraction, and other management purposes. To avoid confusion, we refer to these lands as "open space," as designation as "protected" does not necessarily signify that the area is currently managed to mitigate impacts of invasive species or other threats. Vegetation disturbance was determined using the Habitat Status classes defined in the Carbon Assessment of Hawaii: heavily disturbed (including agricultural and developed lands), mixed native-alien dominated plant communities (defined as non-native dominated in this paper), native dominated plant communities, and bare or sparsely vegetated (<5% plant cover) (Jacobi et al., 2017).

A 250-meter resolution grid was used to partition the study area into four classes for each bias type (Table 3.2). For the accessibility and status biases, class I was comprised of grid cells with a value of 0, and classes II-IV were determined by splitting the remaining cells into terciles. For the disturbance bias classes, we resampled the Habitat Status layer to 250-meter resolution based on the majority class in each 250-meter grid cell. Clustering of 1) all iNaturalist plant records and 2) the iNaturalist and 3) professional agency records for the four study species within these classes was quantified using a bias index as in Kadmon, Farber, & Danin (2004), which compares the observed distribution of records in space to the expected distribution as:

$$Bias_d = \frac{n_d - p_d N}{\sqrt{p_d(1 - p_d)N}}$$

where n_d is the number of species records per class d, p_d is the probability that a record is located in class d given its area, and N is the total number of species records. The index assumes that the probability of a species being observed in a particular class is proportional to the area that the class occupies. Values are distributed like a standard normal variable (Z) and statistically significant ($\alpha = 0.05$) for values greater than 1.64.

Table 3.1
Definitions of native and non-native species status classes.

Class	Definition
Native	Naturally occurring in Hawaii without human assistance
Endemic	Native to and occurring only in Hawaii
Endemic-listed	State and Federally Listed Endangered and Threatened endemic species
Indigenous	Native to Hawaii and occurring elsewhere
Non-native	Introduced to Hawaii by humans (intentional or accidental)
Naturalized	Introduced and now established; not currently considered invasive
Invasive-potential	Introduced and likely to become invasive
Invasive	Introduced and documented to cause significant ecological or economic harm; includes species on the Most Invasive Horticultural Plants list

Table 3.2
Site sampling bias classes, their definitions, and the percentage of the study area that each occupies.

	Accessibility Bias		Status Bias		Disturbance Bias	
Class	Road/trail density (km/km^2)	% Area	Distance to open space (m)	% Area	Disturbance to plant communities	% Area
I	0	79.0%	0	43.5%	Heavily disturbed	16.9%
II	≤ 6.3	7.0%	≤ 579.1	18.8%	Non-native dominated	34.1%
III	≤ 14.8	7.0%	≤ 1729.5	18.8%	Native dominated	31.8%
IV	> 14.8	7.0%	> 1729.5	18.8%	Bare ground	17.2%

3.2.3. Habitat suitability modeling

Model parameters

HSMs were built using observations from iNaturalist and professional agencies with the maxent function in the R package *dismo* v 1.3-3 (Hijmans et al., 2020). Maxent is a popular presence/background correlative modeling method (Guillera-Arroita et al., 2015) that contrasts true species presences with pseudo-absences generated from background data. Restricted background grids can be used to specify areas that were more likely to be surveyed, so that pseudo-absences will theoretically have the same sampling biases as the presences (Merow et al., 2013; Phillips et al., 2009; Syfert et al., 2013). For models based on a single data source, we created restricted backgrounds that included grid cells within 500 meters of a) any research-grade iNaturalist vascular plant species observation or b) any agency record. These two grids were merged to create a restricted background for the combined HSM series. The *dismo* function randomPoints was used to select 10,000 pseudo-absence points from the iNaturalist and combined background grids and 6,000 points from the agency grid (maximum number that could be extracted). All models used logistic output, a regularization multiplier of 2.0, and default settings for remaining parameters.

Models used 250-meter resolution environmental predictors that included the islands of Hawai‘i, Maui, O‘ahu, and Kaua‘i. We initially considered 28 predictors for modeling. Topographic predictors included slope variables (mean, minimum, maximum, range), elevation, and aspect derived from 10-meter resolution digital elevation models (U.S. Geological Survey 3D Elevation Program) and resampled to 250-meters. Nineteen bioclimatic variables were calculated from 250-meter resolution mean monthly temperature and rainfall grids (Giambelluca et al., 2013, 2014). Two normalized difference vegetation index (NDVI) variables, dry-season NDVI (JJA 2020) and NDVI amplitude (the difference between the maximum and minimum NDVI values per pixel in 2020) were derived from the global 250-meter MODIS/Terra product MOD13Q1 v006. NDVI is often used as a proxy of photosynthetic activity, vegetation density, or productivity (Pettorelli, 2013). Finally, a categorical soil great group variable was created by converting survey data from the U.S. Department of Agriculture, Natural Resources

Conservation Service (2020) to raster based on maximum combined area. Correlation analysis was performed to identify and remove highly collinear continuous variables (|r|> 0.7), which narrowed the final set of predictors down to ten: elevation, mean slope, aspect, isothermality, temperature annual range, precipitation seasonality, precipitation of the warmest quarter, dry-season NDVI, NDVI amplitude, and soil great group.

Model series and filtering treatments

To examine the effect of data source and spatial filtering on estimates of suitable habitat, we produced seven models for each of the four invasive study species (Table 3.3). All models used the Maxent default setting for removing duplicate observations that occur within a single grid cell (determined by the 250-meter resolution of the environmental layers). iNaturalist unfiltered and agency unfiltered HSMs used all available records from their respective sources, while the combined unfiltered HSM used all available records for a given species from both sources.

We applied four filtering treatments to the iNaturalist data, one targeting clustering in geographic space and three targeting the environmental biases described previously. Subsampling for the iNaturalist thinned HSM was similar in concept to the Maxent removal of duplicate records, but further reduced spatial clustering by selecting iNaturalist records at a coarser resolution than that of the predictor layers (one record per 1-kilometer cell). For the iNaturalist accessibility-stratified, iNaturalist status-stratified, and iNaturalist disturbance-stratified HSMs, we created environmentally stratified subsamples proportionate to the area of each site class. These stratified treatments aimed to remove potentially redundant records in oversampled site classes (Varela et al., 2014). Pseudo-absence points for filtered models were drawn from the iNaturalist background grid.

Table 3.3
Total observations available from each data source (shaded columns) and the number of records used in each habitat suitability model (HSM) series. iNat = iNaturalist unfiltered HSM, iNat_1km = iNaturalist thinned HSM, iNat_access = iNaturalist accessibility-stratified HSM, iNat_status = iNaturalist status-stratified HSM, iNat_disturb = iNaturalist disturbance-stratified HSM, Agency = agency HSM, Combined = combined HSM.

Species	Total iNaturalist records	iNat	iNat_ 1km	iNat_ access	iNat_ status	iNat_ disturb	Total agency records	Agency	Combined
Hedychium gardnerianum	152	110	96	47	57	92	215	126	235
Lantana camara	165	131	124	80	109	76	230	154	282
Leucaena leucocephala	296	246	228	112	149	31	497	104	345
Psidium cattleianum	167	129	116	64	57	76	937	527	656

Comparing predictions

The objective of model comparison and evaluation was to observe the effects of data source and filtering treatment on predictions, rather than to identify the “best” or most accurate model. We were particularly interested in observing similarity between single-source models (i.e. iNaturalist-only versus agency-only, where high similarity would suggest that observations represented similar environments), single-source and combined models (if the combined HSM were more similar to either the iNaturalist-only or agency-only HSM, that could indicate that that source contained more comprehensive environmental information), and unfiltered and filtered iNaturalist models (high similarity between these models would suggest limited ability of this practice to reduce sampling bias).

We used Schoener’s *D*, an index that measures overlap between potential species distributions with values ranging from 0 (no overlap) to 1 (complete overlap) (Warren et al., 2008), to estimate similarity among the HSM predictions. It has been shown to outperform other similarity metrics such as Warren’s *I* (Brown & Carnaval, 2019; Rödder & Engler, 2011).

Pairwise Schoener's *D* values were calculated between full models and within each site sampling bias class using the R package *ENMeval* (Muscarella et al., 2014).

Models were also compared using threshold-dependent measures and predictor contributions. The maximum sum of sensitivity and specificity threshold, recommended because it minimizes omission and commission errors and its selection is less affected by the use of pseudo-absences (Liu et al., 2005, 2013, 2016), was used to calculate total suitable area predicted by each HSM series (as a percentage of study area). In order to observe whether bias in the species records would lead to similar biases in model predictions, we also calculated the distribution of suitable cells among site classes. Finally, Maxent tracks the contribution of each environmental predictor to model gain and reports their relative contributions as percentage (Phillips, 2017). We used the predictors' percent contribution to each HSM as another indicator of how independent sets of observations influenced model training. The maximum sum of sensitivity and specificity threshold was then used to identify the range of suitable values for top contributing predictors.

3.3. Results

3.3.1. Native status sampling bias

We obtained 13,186 iNaturalist research-grade records for 253 vascular plant species that were collected by 1,506 unique users. Though non-native species represent just 54.9% (n = 1620) of Hawaiian plant taxa, they represented 74.7% (n = 189) of species observed by iNaturalist observers (Fig. 3.2). Endemic species, particularly those that are State or Federally listed, were under-sampled in terms of both number of taxa and total records, and just three species accounted for 59.0% of all endemic plant records: *Metrosideros polymorpha* (664 records), *Argyroxiphium sandwicense* (198), and *Vaccinium reticulatum* (186). Among non-native taxa, iNaturalist observers were more likely to record Polynesian introductions and species classified as invasive (Fig. 3.2). Invasive plant species represent only 7.9% of all Hawaiian plants, but 20.6% of the observed species and 24.7% of total iNaturalist records.

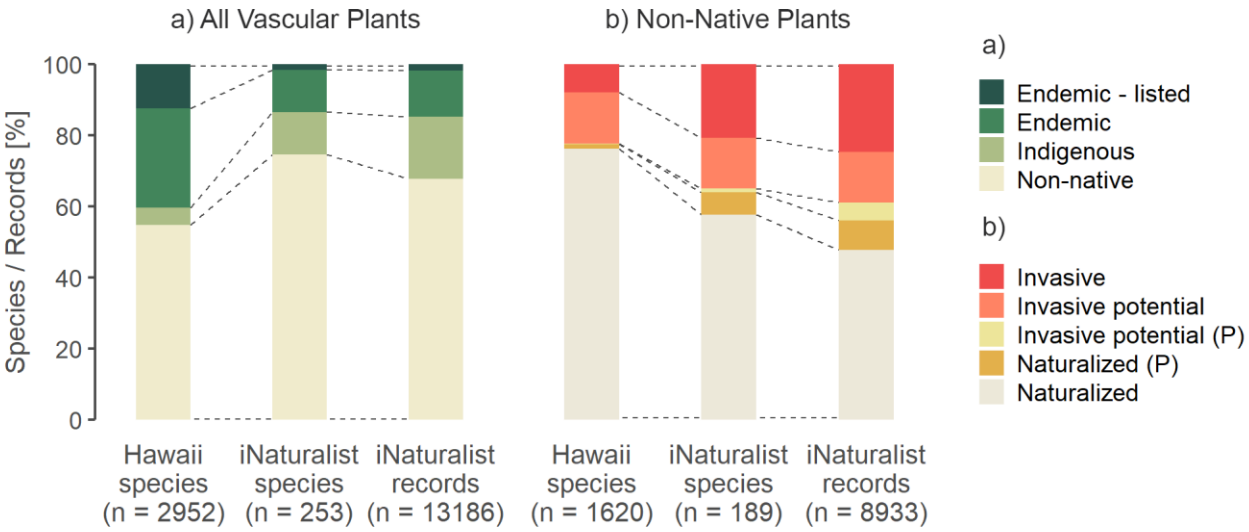

Figure 3.2
Endemic native, indigenous native, and non-native species as a proportion of all plant species occurring on Hawaii's four largest islands, and their representation in iNaturalist research-grade observations. Endemic - listed refers to species listed as Threatened or Endangered at the state or federal level. Non-native species are further classified by invasiveness. (P) = Polynesian introduction.

3.3.2. Site sampling bias

iNaturalist plant observations were generally biased toward road/trail accessible locations, sites in or near designated open spaces, and sites with heavily disturbed or non-native dominated vegetation. Bias toward areas with road or trail access (classes II-IV) was particularly strong among non-native species (Fig. 3.3a). These sites represented 21.0% of the study area, but contained 57.9% of iNaturalist records. Sites further from open space (III-IV) were significantly underrepresented for all plant species (Fig. 3.3b). Overrepresentation of open space was particularly strong for endemic species, for which 59.4% of records occurred in status class I. Record distribution among disturbance classes (Fig. 3.3c) was rather unsurprising: all species were underrepresented in the bare or sparsely vegetated class (IV) and, with the exception of endemic species, biased toward the heavily disturbed and non-native classes (I-II). Endemic species were most intensely sampled in the native class (III).

iNaturalist records for the four study species consistently demonstrated the same site sampling biases as the overall dataset: significant underrepresentation of road/trail-free cells (Fig. 3.4a), cells furthest away from open space (Fig. 3.4b), and the native dominated class (with the exception of *H. gardnerianum*) (Fig. 3.4c). Records collected by agencies showed similar status bias, but different patterns for accessibility and disturbance. Agency data for *H. gardnerianum* and *P. cattleianum* exhibited a sampling pattern opposite those of iNaturalist: overrepresentation of the road/trail-free class and underrepresentation of more accessible sites. The majority of *L. camara* and *L. leucocephala* agency records also came from the road/trail-free class, though it was not significantly oversampled. Among disturbance classes, agency sampling was more strongly skewed toward the native dominated class (III) for all four species, with significant undersampling in heavily disturbed sites. However, *L. camara* and *L. leucocephala* agency sampling was similar to iNaturalist in the non-native dominated class (II).

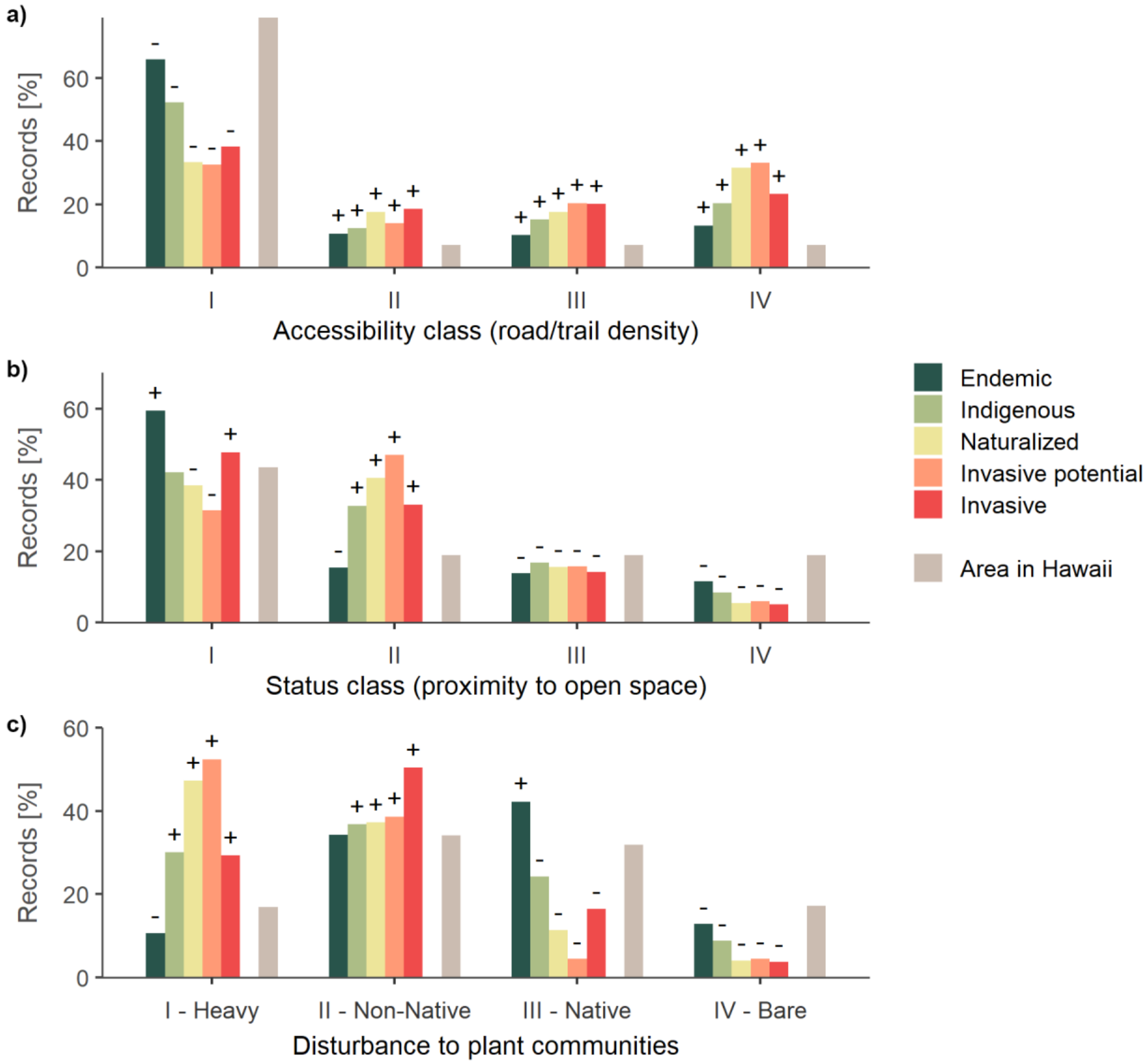

Figure 3.3
Distribution of iNaturalist records by (a) accessibility (class I = no roads), (b) status (I = within designated open space), and (c) disturbance. Gray bars indicate % area represented by each class. +/- indicate significant over/underrepresentation.

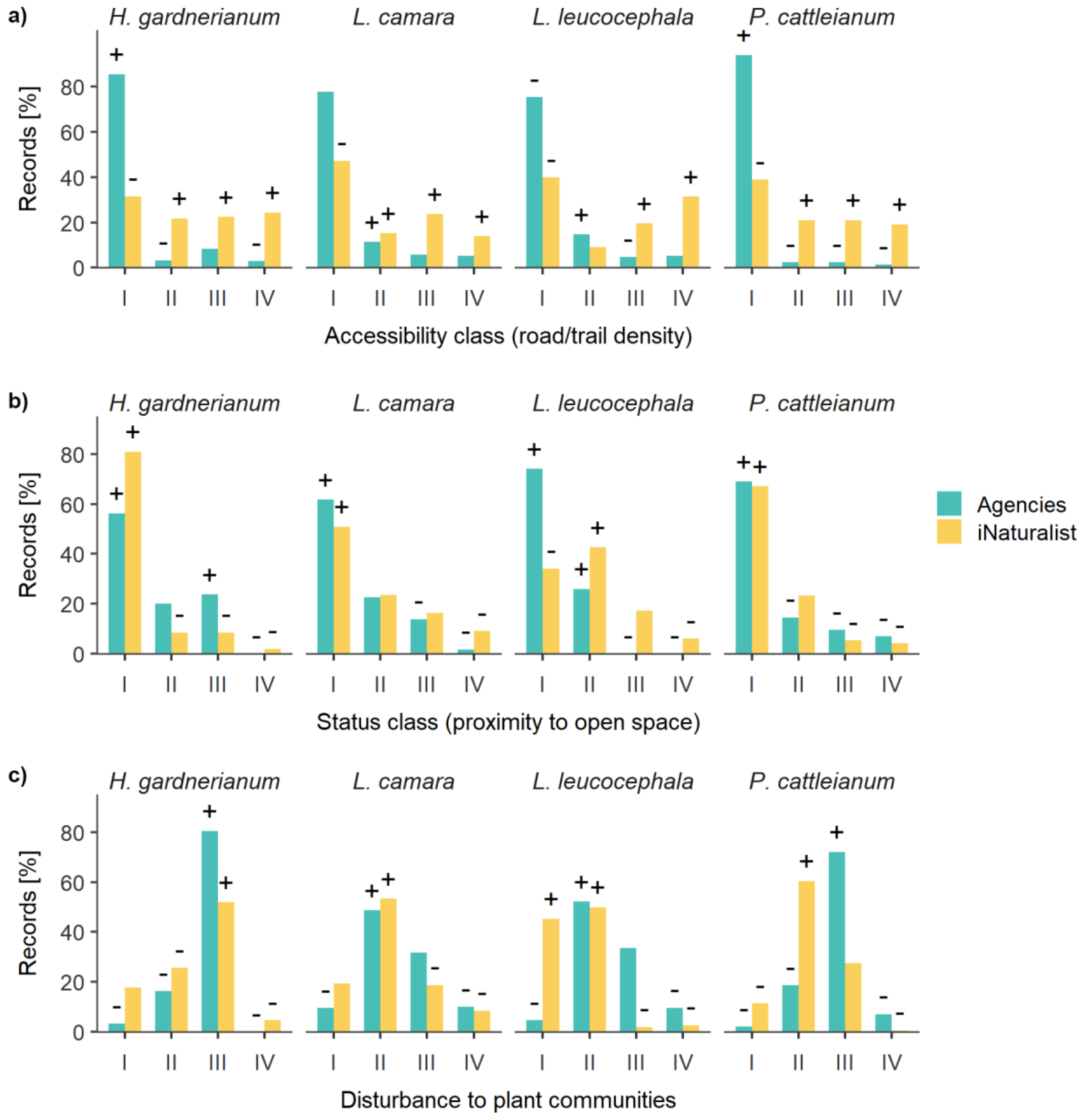

Figure 3.4

(a) Accessibility bias (class I = no roads or trails), (b) status bias (I = within designated open space), and (c) disturbance bias in iNaturalist vs. management agency records for four invasive species. +/- indicate significant over/underrepresentation.

3.3.3. Model comparison

Model similarity

Overlap was lowest between iNaturalist- and agency-only models (i.e. single-source HSMs) (D = 0.42-0.74) (Fig. 3.5), with relatively lower D scores within site classes depending on the species (Appendix B, Fig. B2). For *H. gardnerianum*, *L. camara,* and *P. cattleianum*, overlap between the single-source HSMs was lowest in the bare ground class. For *L. camara* and *L. leucocephala*, there were greater differences between the single-source HSMs within the native-dominated class and in sites with low to zero road/trail density.

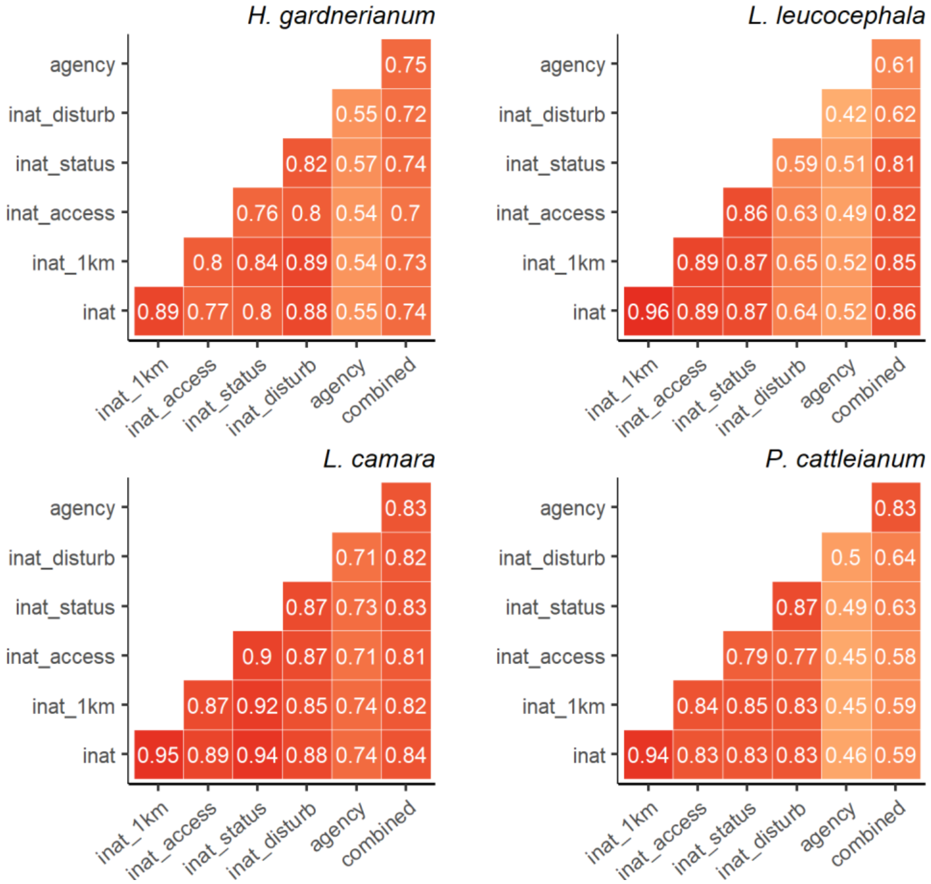

Figure 3.5

Similarity or overlap (pairwise Schoener's *D* index) between habitat suitability models (HSMs), where 0 signifies no overlap and 1 is complete overlap. inat = iNaturalist unfiltered HSM, inat_1km = iNaturalist thinned HSM, inat_access = iNaturalist accessibility-stratified HSM, inat_status = iNaturalist status-stratified HSM, inat_disturb = iNaturalist disturbance-stratified HSM, agency = agency HSM, combined = combined HSM.

Similarity between single-source and combined models also varied by species. The *L. leucocephala* combined HSM had higher overlap with the iNaturalist model across all site classes, while the *P. cattleianum* combined HSM was more similar to the agency HSM, particularly in open spaces and road-free, native-dominated, and bare ground sites (Appendix B,

Fig. B3). Single-source HSMs for both *H. gardnerianum* and *L. camara* had similar, moderate overlap with their respective combined HSMs (Fig. 3.5).

The highest overlap occurred between unfiltered and thinned iNaturalist models ($D \geq 0.89$), with high *D* scores observed across all site classes (Appendix B, Fig. B4). Moderate to high overlap was also observed between the unfiltered and filtered models, with *D* ranging from 0.59 to 0.94. Within site classes, the filtering treatments did not consistently reduce similarity between unfiltered and filtered/thinned iNaturalist models.

Suitable area

Predictions of percent suitable area varied among HSMs by as little as 10.4 percentage points (*H. gardnerianum*) and as much as 29.2 percentage points (*P. cattleianum*) (Fig. 3.6). Neither the iNaturalist unfiltered nor agency models consistently predicted higher estimates of suitable area, and the two datasets produced different estimates of suitable area across the four islands (Appendix B, Fig. B5). The distribution of suitable area among disturbance classes was similar to that of the iNaturalist and agency observations, most notably for *P. cattleianum* and *L. leucocephala*. However, suitable area was similarly distributed among accessibility and status classes (with the exception of *P. cattleianum*) regardless of sampling patterns in the observations.

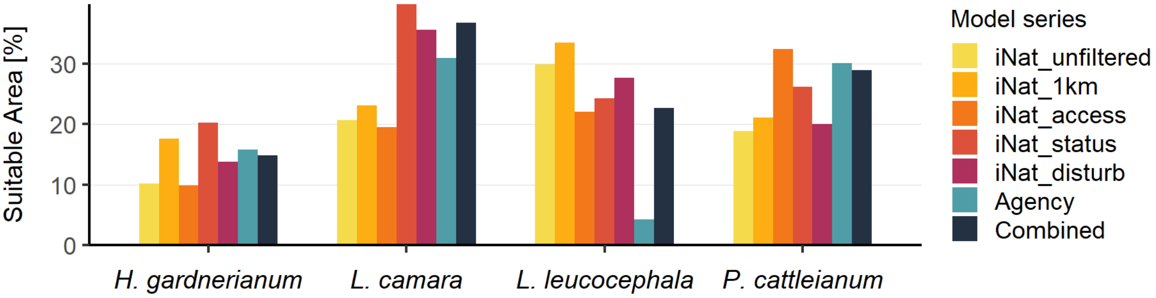

Figure 3.6
Predicted suitable area (as a percentage of the study area) for each HSM series.

The iNaturalist thinning treatment produced slight increases in predictions of suitable area (2.2-7.4 percentage points), but the effect of stratified filtering was less consistent across species. Though total estimates differed between unfiltered and filtered iNaturalist HSMs, the distribution of suitable area among site classes was often similar (Fig. 3.7). For example, though the status-stratified HSM increased total estimates of suitable area for species that had been significantly oversampled in open spaces (status class I), there was no significant difference in how that suitable area was distributed. There were a few exceptions in which stratified iNaturalist HSMs increased predicted suitable area in undersampled classes, such as the disturbance-stratified HSMs for *L. camara*, *L. leucocephala*, and *P. cattleianum* (Fig. 3.4c), which increased estimates of suitable area in native-dominated sites.

Environmental predictors

Environmental predictors made different relative percent contributions to models of the same species (Appendix B, Fig. B6). Climate variables (rainfall of the warmest quarter and temperature annual range) made higher contributions to the *L. camara* and *P. cattleianum* agency and combined models, and were less important in iNaturalist-based HSMs for these species. Models of *H. gardnerianum* and *L. leucocephala* shared some top predictors (elevation and soil great group), but there were still differences in the percent contribution of these variables.

Predictor values classified as suitable varied among models of the same species (Appendix B, Fig. B7). For example, the *L. camara* agency HSM predicted a wider range of suitable elevation values, but a narrower range of rainfall values than the iNaturalist HSM. Filtering treatments had a similar effect that varied by species. Accessibility-stratified HSMs produced narrower ranges of suitable elevation values for *H. gardnerianum* and *L. leucocephala*, but wider ranges for *L. camara* and *P. cattleianum*.

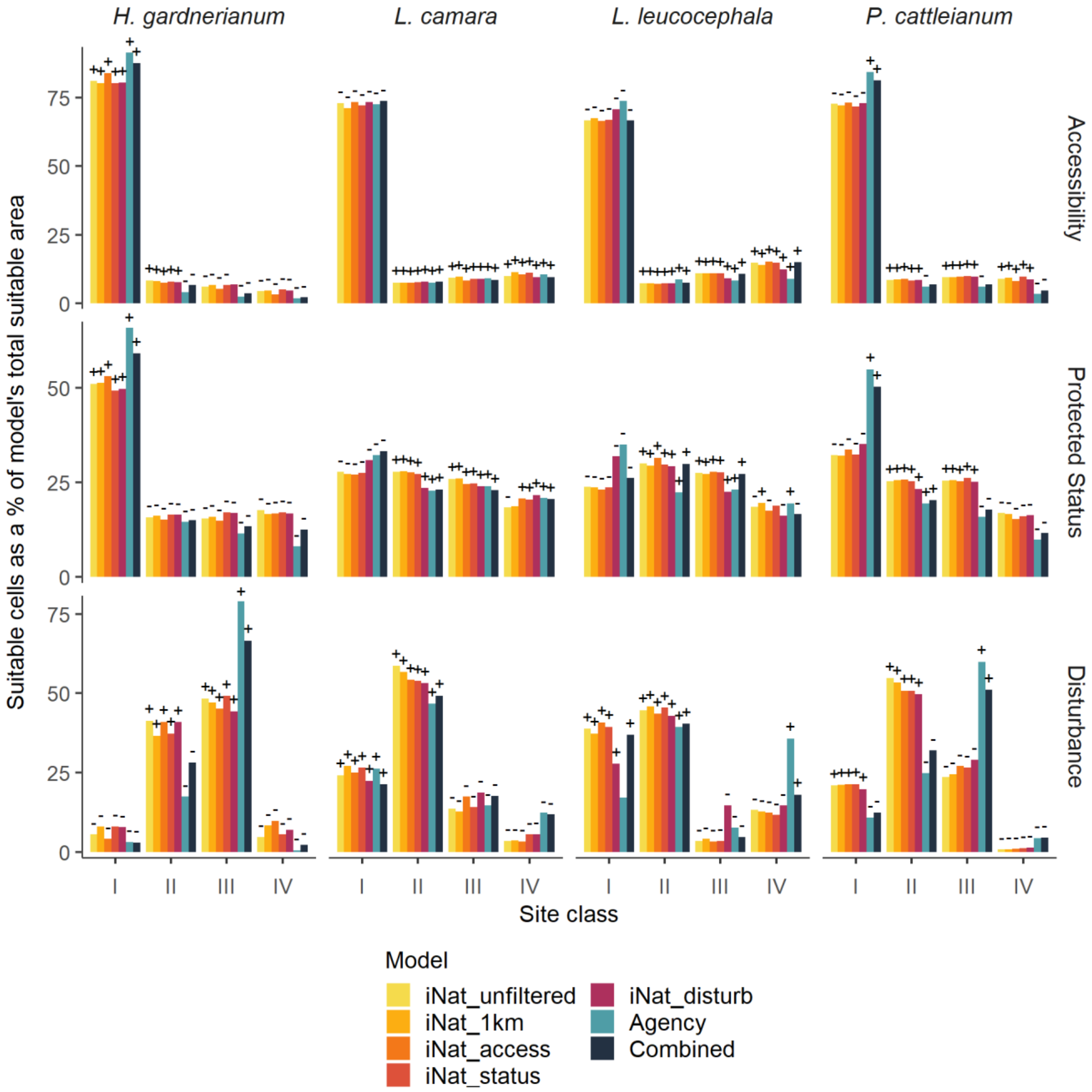

Figure 3.7

Distribution of each HSM's suitable cells by site accessibility, status, and disturbance. +/- indicate significant over/underrepresentation.

3.4. Discussion

3.4.1. iNaturalist bias toward non-native species

Observer preference for rare species has been observed in studies of other taxonomic groups. Citizen scientists have been more motivated to survey areas where threatened bird species are known to occur (Tulloch et al., 2013), and tend to underreport more common butterfly species (Matteson et al., 2012). However, we found that non-native species represented the majority of iNaturalist plant species and observations, while endemic Hawaiian plants were underrepresented. Though a high proportion of Hawaiian plants are threatened or endangered, only four species were recorded (Fig. 3.2).

This is perhaps unsurprising in Hawaii, where non-native species currently dominate native Hawaiian flora both in terms of species richness and land area (with the exception of the Big Island) (Hughes et al., 2017). Frequent encounters with rare, threatened, or endangered plants would be unexpected given the more restricted ranges and smaller population sizes of native island species in general (Paulay, 1994). Furthermore, species-level plant identification can be difficult (Roman et al., 2017), and citizen scientists may be more likely to record larger and more widely distributed plant species that are easier to identify (Boakes et al., 2016). For iNaturalist in Hawaii, the most-recorded plants were ʻōhiʻa (*Metrosideros polymorpha*), an abundant endemic tree; beach naupaka (*Scaevola sericea*), a common coastal native also used in commercial and residential plantings; and noni (*Morinda citrifolia*), a Polynesian introduction with numerous cultural uses. Each of these woody species would be familiar to local observers, and, for plants, this familiarity may be as motivating as rarity for other taxa (Boakes et al., 2016).

Species considered invasive or potentially invasive were recorded at a higher rate than other non-native plants. They represented 12.3% of all plant species in Hawaii, but 26.9% of the species recorded by iNaturalists and 29.8% of the observations. This could indicate that invasive species are more common than native species in areas surveyed by iNaturalists, but a fuller analysis of native vs. non-native species bias would need to account for prevalence, which this study did not do. It may also suggest that iNaturalist observers are more motivated or able to record these taxa. While invasive species have received a fair amount of media coverage in Hawaii, a 2003 survey showed that the general public is relatively unconcerned about invasive plants (Daehler, 2008). Residents may also have positive associations with certain species. Kukui (*Aleurites moluccana*), for example, is the Hawaiian state tree and a Polynesian introduction with invasive potential (Daehler et al., 2004). Other invasive trees have gained emotional or cultural value as well, including *P. cattleianum* (Warner & Kinslow, 2013) and the early 20th century introduction *Falcataria moluccana* (Niemiec et al., 2017). Whatever the motivation, the relative abundance of non-native plant records on iNaturalist is encouraging for invasive species management purposes.

3.4.2. Spatial sampling bias

The iNaturalist data showed significant sampling biases toward open space and cells with higher road/trail density, which is consistent with other citizen science datasets (Botts et al., 2011; Mair & Ruete, 2016; Tulloch et al., 2013). Observations were also skewed toward heavily disturbed and non-native dominated sites. These sampling patterns were not unexpected, especially for non-native plant species, and it is possible that they reflect the species actual distribution or abundance rather than observation bias. Roads often serve as a dispersal pathway (Pauchard et al., 2009) and source of ignition for fire-prone invasive species (Ellsworth et al., 2014), and *L. camara* presence has been shown to be positively associated with roadside disturbance (August-Schmidt et al., 2015).

Yet, if that were the case, one might expect the independent records from the professional agencies to corroborate the iNaturalist data. But accessibility sampling patterns in the agency records were either less pronounced than (*L. camara, L. leucocephala*) or the inverse (*H. gardnerianum, P. cattleianum*) of those in iNaturalist. Both datasets were similarly skewed toward open space and adjacent sites, but differed in the proportion of records observed in each status class, particularly for *L. leucocephala* and *H. gardnerianum* (Fig. 3.4b). iNaturalists made far fewer observations in native-dominated sites compared to agencies, which in turn tended to undersample heavily disturbed sites (Fig. 3.4c). This disagreement indicates some degree of bias in at least one of the two sources, and that each dataset represents distinct environments.

These biases could affect HSM accuracy if the oversampled classes do not include a range of environmental conditions occupied by the species. This appeared to be the case for disturbance bias, as oversampling in the heavily disturbed, non-native dominated, and native dominated classes was associated with disagreement between single-source models in how suitable area was distributed. But we did not find a consistent relationship between accessibility and status sampling bias patterns and distribution of suitable habitat. Rather, models for *H. gardnerianum*, *L. camara*, and *L. leucocephala* generally agreed with each other regardless of the sampling bias in the training records. This suggests that open space and road/trail networks in Hawaii encompass a range of environmental gradients relevant to the study species, and thus observer preference for these sites does not necessarily restrict the utility of those observations (Kadmon et al., 2004; McCarthy et al., 2012). However, it may be important to investigate filtering treatments and/or complementary datasets when sampling data is biased with respect to vegetation disturbance.

3.4.3. Effect of filtering treatments on iNaturalist HSMs

The thinning treatment produced HSMs that were highly similar to unfiltered iNaturalist HSMs, and had limited impact on predictions of suitable area and variable contributions. Other papers have observed that similar thinning treatments can either improve model performance by reducing overfitting (Boria et al., 2014; Fourcade et al., 2014) or decrease performance due to the random approach as well as loss of information (Steen et al., 2021; Varela et al., 2014). In this study, it is possible that thinning to a 1-kilometer resolution was not coarse enough to impact the models beyond small increases in estimated suitable area. Relatively few records were removed from training at this resolution, especially compared to the other filtering treatments.

Targeting clusters in environmental space, rather than thinning records geographically, is believed to have a more positive effect on model performance, but smaller datasets may also produce less consistent results (Varela et al., 2014). The effects of stratified filtering treatments in this study varied by bias type, with the most notable impact observed for disturbance bias. Disturbance-stratified HSMs increased relative predictions of suitable area in the native-dominated class for the three species that were undersampled in that class. The accessibility-stratified HSM of *H. gardnerianum* also produced a small increase in the proportion of suitable area in the undersampled road/trail-free class. These examples imply that stratified filtering can influence target biases in model predictions and increase habitat estimates in undersampled environments, but this outcome was not consistent. For the most part, filtered HSMs maintained similar distributions of suitable area as well as moderate to high overlap with the unfiltered iNaturalist HSM. This could indicate that the stratified treatments were not effective a given species, or, in conjunction with our previously discussed results, that certain sampling biases do not correspond to biases in more meaningful environmental variables.

Reduced sample sizes due to filtering were often associated with greater divergence from the unfiltered model. While a smaller, evenly-sampled dataset has been found to be more effective than a larger, biased one (Bean et al., 2012; Varela et al., 2014), sample size does have a significant effect on HSM performance (Gábor et al., 2020), and thus small samples may be further negatively impacted by environmental filtering. We observed a strong negative correlation between percent decrease in sample size and overlap with the unfiltered HSM, i.e. the more records were filtered out, the less similar the iNaturalist models became. It is thus difficult to determine whether the departures from the unfiltered HSMs are due to targeted filtering or the loss of training data. Future work should control for sample size (e.g. as in Boria et al., 2014), to more clearly distinguish between the effects of filtering, data source, and information loss.

3.4.4. Complementary monitoring

Though often fewer in number, iNaturalist observations covered a similarly broad range of conditions and were a valuable supplement to the relatively more structured, professional data for the example invasive species in this study. iNaturalist observers and professional agencies also appeared to capture unique environmental conditions, as demonstrated by the suitable predictor values and moderate overlap between single-source HSMs. Neither source appeared to consistently provide more comprehensive information or have greater similarity to the combined HSM, despite the higher number of agency records for three of the species (Table 3.3). When agency and iNaturalist sample sizes differed greatly, it is possible that the combined HSM was simply more similar to the source that contributed more training records. For example, there were four times as many agency observations for *P. cattleianum*. However, iNaturalists sampled *P. cattleianum* more evenly across the islands and contributed to greater predictions of suitable area on Oʻahu and Kauaʻi in the combined HSM (Appendix B, Fig. B5).

Previous studies have noted that well-designed citizen science programs can collect data comparable to that of professional scientists (Chandler et al., 2017), and that combining structured survey data with eBird records improves model accuracy (Robinson et al., 2020). We found that incidental iNaturalist observations are useful in filling the gaps in professional survey data, particularly with respect to vegetation disturbance. Citizen science bias toward disturbed and non-native dominated sites and professional bias toward native-dominated sites were reproduced in model predictions, which, in addition to highlighting the limitations of correlative HSMs in approximating species niches, has practical implications for HSMs as a management tool. Underestimates of invasive species distributions could limit land managers’ ability to identify vulnerable areas and prioritize monitoring efforts. Citizen science data could be critical in monitoring areas that have not been officially surveyed.

Conversely, remote areas of the Hawaii region were poorly sampled in iNaturalist. Kahoʻolawe, Lānaʻi, Molokaʻi, and Niʻihau were excluded from this analysis, but the extremely low number of iNaturalist plant observations on these smaller, sparsely populated islands demonstrates an obvious limitation of low-structure citizen science data, which is that sampling is largely restricted to public access areas. Management agencies seeking to utilize citizen science as a complementary data source may use this known bias to prioritize their own survey resources. Additionally, when citizen science observations are the only monitoring data available for a region, care should be taken when interpreting the significance of unsampled space.

Though we did not seek to identify the “best” model for each species, it is evident that iNaturalist and professional observations, on their own, produced differing estimates of suitable habitat (Appendix B, Fig. B5). To take advantage of biased yet complementary survey efforts, we simply combined or ‘pooled’ all available data. However, more formal integrated modeling approaches may be able to better address sampling biases while more fully preserving the specific strengths of each dataset (Dorazio, 2014; Fletcher et al., 2019; Isaac et al., 2020; Miller et al., 2019; Pacifici et al., 2017). Utilizing additional attributes of the iNaturalist data could also improve the modeling process. Though absence records are lacking in iNaturalist, observer records of non-target species could be used to infer absence and select more meaningful pseudo-absences (Bradter et al., 2018; Milanesi et al., 2020). This observer data is readily accessible in iNaturalist and could improve model accuracy.

3.5. Conclusion

iNaturalist observers have made thousands of plant observations in Hawaii and preferentially record non-native and invasive species. These observations are not free of sampling biases that affect other citizen science databases; records were more likely to be made in open spaces and relatively more accessible, disturbed areas. However, occurrence data from regional agencies exhibited similar or inverse sampling patterns. When these datasets were used to build HSMs, each data source appeared to sample distinct environments, yet neither consistently produced more comprehensive predictions. Low-structure citizen science programs like iNaturalist thus provide a valuable source of species occurrence data, however opportunistic or incidental, that can complement geographically limited surveys of expert scientists. Filtering may increase estimates of suitable habitat in undersampled sites, but may not be necessary if features of interest, like the road/trail network and open spaces examined here, are inclusive of a range of environmental conditions important to the species in question. We recommend examining and including all available data regardless of suspected anthropogenic sampling biases.

Acknowledgments

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References

August-Schmidt, E. M., Haro, G., Bontrager, A., & D'Antonio, C. M. (2015). Preferential associations of invasive *Lantana camara* (Verbenaceae) in a seasonally dry Hawaiian woodland. *Pacific Science, 69*(3), 385–397. doi:10.2984/69.3.7

Bean, W. T., Stafford, R., & Brashares, J. S. (2012). The effects of small sample size and sample bias on threshold selection and accuracy assessment of species distribution models. *Ecography, 35*(3), 250–258. doi:10.1111/j.1600-0587.2011.06545.x

Beck, J., Böller, M., Erhardt, A., & Schwanghart, W. (2014). Spatial bias in the GBIF database and its effect on modeling species' geographic distributions. *Ecological Informatics, 19,* 10–15. doi:10.1016/j.ecoinf.2013.11.002

Björklund, N., Lindelöw, Å., & Schroeder, L. M. (2016). Erroneous conclusions about current geographical distribution and future expansion of forest insects in Northern Sweden: Comments on Hof and Svahlin (2015). *Scandinavian Journal of Forest Research, 31*(1), 126–127. doi:10.1080/02827581.2015.1086018

Boakes, E. H., Gliozzo, G., Seymour, V., Harvey, M., Smith, C., Roy, D. B., & Haklay, M. (2016). Patterns of contribution to citizen science biodiversity projects increase understanding of volunteers' recording behaviour. *Scientific Reports, 6*(1), 33051. doi:10.1038/srep33051

Boakes, E. H., McGowan, P. J. K., Fuller, R. A., Chang-qing, D., Clark, N. E., O'Connor, K., & Mace, G. M. (2010). Distorted views of biodiversity: Spatial and temporal bias in species occurrence data. *PLoS Biology, 8*(6), e1000385. doi:10.1371/journal.pbio.1000385

Boria, R. A., Olson, L. E., Goodman, S. M., & Anderson, R. P. (2014). Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. *Ecological Modelling, 275,* 73–77. doi:10.1016/j.ecolmodel.2013.12.012

Botts, E. A., Erasmus, B. F. N., & Alexander, G. J. (2011). Geographic sampling bias in the South African Frog Atlas Project: Implications for conservation planning. *Biodiversity and Conservation, 20*(1), 119–139. doi:10.1007/s10531-010-9950-6

Bradter, U., Mair, L., Jönsson, M., Knape, J., Singer, A., & Snäll, T. (2018). Can opportunistically collected Citizen Science data fill a data gap for habitat suitability models of less common species? *Methods in Ecology and Evolution, 9*(7), 1667–1678. doi:10.1111/2041-210X.13012

Brown, J. L., & Carnaval, A. C. (2019). A tale of two niches: Methods, concepts, and evolution. *Frontiers of Biogeography, 11*(4). doi:10.21425/F5FBG44158

Carlquist, S. J. (1974). *Island biology*. Columbia University Press.

Chandler, M., See, L., Copas, K., Bonde, A. M. Z., López, B. C., Danielsen, F., Legind, J. K., Masinde, S., Miller-Rushing, A. J., Newman, G., Rosemartin, A., & Turak, E. (2017). Contribution of citizen science towards international biodiversity monitoring. *Biological Conservation*, *213*, 280–294. doi:10.1016/j.biocon.2016.09.004

Coxen, C. L., Frey, J. K., Carleton, S. A., & Collins, D. P. (2017). Species distribution models for a migratory bird based on citizen science and satellite tracking data. *Global Ecology and Conservation*, *11*, 298–311. doi:10.1016/j.gecco.2017.08.001

Crall, A. W., Jarnevich, C. S., Young, N. E., Panke, B. J., Renz, M., & Stohlgren, T. J. (2015). Citizen science contributes to our knowledge of invasive plant species distributions. *Biological Invasions*, *17*(8), 2415-2427.

Crall, A. W., Newman, G. J., Stohlgren, T. J., Holfelder, K. A., Graham, J., & Waller, D. M. (2011). Assessing citizen science data quality: An invasive species case study: Assessing citizen science data quality. *Conservation Letters*, *4*(6), 433–442. doi:10.1111/j.1755-263X.2011.00196.x

Cuddihy, L. W., & Stone, C. P. (1990). *Alteration of native Hawaiian vegetation: Effects of humans, their activities and introductions*. University of Hawaii, Cooperative National Park Resources Studies Unit. https://pcsuhawaii.org/books-1990/

Daehler, C. C. (2008). Invasive plant problems in the Hawaiian Islands and beyond: Insights from history and psychology. In *Plant Invasions: Human perception, ecological impacts and management* (pp. 3–20). Backhuys Publishing.

Daehler, C. C., Denslow, J. S., Ansari, S., & Kuo, H.-C. (2004). A Risk-Assessment System for Screening Out Invasive Pest Plants from Hawaii and Other Pacific Islands. *Conservation Biology*, *18*(2), 360–368. doi:10.1111/j.1523-1739.2004.00066.x

Danielsen, F., Jensen, P. M., Burgess, N. D., Altamirano, R., Alviola, P. A., Andrianandrasana, H., Brashares, J. S., Burton, A. C., Coronado, I., Corpuz, N., Enghoff, M., Fjeldså, J., Funder, M., Holt, S., Hübertz, H., Jensen, A. E., Lewis, R., Massao, J., Mendoza, M. M., … Young, R. (2014). A Multicountry Assessment of Tropical Resource Monitoring by Local Communities. *BioScience*, *64*(3), 236–251. doi:10.1093/biosci/biu001

Daru, B. H., Park, D. S., Primack, R. B., Willis, C. G., Barrington, D. S., Whitfeld, T. J. S., Seidler, T. G., Sweeney, P. W., Foster, D. R., Ellison, A. M., & Davis, C. C. (2018). Widespread sampling biases in herbaria revealed from large-scale digitization. *New Phytologist*, *217*(2), 939–955. doi:10.1111/nph.14855

Di Cecco, G. J., Barve, V., Belitz, M. W., Stucky, B. J., Guralnick, R. P., & Hurlbert, A. H. (2021). Observing the Observers: How Participants Contribute Data to iNaturalist and Implications for Biodiversity Science. *BioScience*, *71*(11), 1179–1188. doi:10.1093/biosci/biab093

Dickinson, J. L., Zuckerberg, B., & Bonter, D. N. (2010). Citizen Science as an Ecological Research Tool: Challenges and Benefits. *Annual Review of Ecology, Evolution, and Systematics*, *41*(1), 149–172. doi:10.1146/annurev-ecolsys-102209-144636

Dorazio, R. M. (2014). Accounting for imperfect detection and survey bias in statistical analysis of presence-only data. *Global Ecology and Biogeography*, *23*(12), 1472–1484. doi:10.1111/geb.12216

Ellsworth, L. M., Litton, C. M., Dale, A. P., & Miura, T. (2014). Invasive grasses change landscape structure and fire behaviour in Hawaii. *Applied Vegetation Science*, *17*(4), 680–689. doi:10.1111/avsc.12110

Farhadinia, M. S., Moll, R. J., Montgomery, R. A., Ashrafi, S., Johnson, P. J., Hunter, L. T. B., & Macdonald, D. W. (2018). Citizen science data facilitate monitoring of rare large carnivores in remote montane landscapes. *Ecological Indicators*, *94*, 283–291. doi:10.1016/j.ecolind.2018.06.064

Feldman, M. J., Imbeau, L., Marchand, P., Mazerolle, M. J., Darveau, M., & Fenton, N. J. (2021). Trends and gaps in the use of citizen science derived data as input for species distribution models: A quantitative review. *PLOS ONE*, *16*(3), e0234587. doi:10.1371/journal.pone.0234587

Fletcher, R. J., Hefley, T. J., Robertson, E. P., Zuckerberg, B., McCleery, R. A., & Dorazio, R. M. (2019). A practical guide for combining data to model species distributions. *Ecology*, e02710. doi:10.1002/ecy.2710

Fourcade, Y., Engler, J. O., Rödder, D., & Secondi, J. (2014). Mapping species distributions with Maxent using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. *PLoS ONE*, *9*(5), e97122. doi:10.1371/journal.pone.0097122

Freitag, A., Meyer, R., & Whiteman, L. (2016). Strategies Employed by Citizen Science Programs to Increase the Credibility of Their Data. *Citizen Science: Theory and Practice*, *1*(1), 2. doi:10.5334/cstp.6

Gábor, L., Moudrý, V., Barták, V., & Lecours, V. (2020). How do species and data characteristics affect species distribution models and when to use environmental filtering? *International Journal of Geographical Information Science*, *34*(8), 1567–1584. doi:10.1080/13658816.2019.1615070

GBIF.org. (2020). *GBIF Occurrence Download* (p. 1470749) [Darwin Core Archive]. The Global Biodiversity Information Facility. doi:10.15468/DL.243P7M

Giambelluca, T. W., Chen, Q., Frazier, A. G., Price, J. P., Chen, Y.-L., Chu, P.-S., Eischeid, J. K., & Delparte, D. M. (2013). Online Rainfall Atlas of Hawaiʻi. *Bulletin of the American Meteorological Society*, *94*(3), 313–316. doi:10.1175/BAMS-D-11-00228.1

Giambelluca, T. W., Shuai, X., Barnes, M. L., Alliss, R. J., Longman, R. J., Miura, T., Chen, Q., Frazier, A. G., Mudd, R. G., Cuo, L., & Businger, A. D. (2014). *Evapotranspiration of Hawaiʻi. Final report submitted to the U.S. Army Corps of Engineers—Honolulu District, and the Commission on Water Resource Management, State of Hawaiʻi*.

Gillespie, T. W., Chu, J., & Pau, S. (2008). Non-native plant invasion of the Hawaiian Islands. *Geography Compass*, *2*(5), 1241–1265. doi:10.1111/j.1749-8198.2008.00152.x

Groom, Q., Desmet, P., Reyserhove, L., Adriaens, T., Oldoni, D., Vanderhoeven, S., Baskauf, S. J., Chapman, A., McGeoch, M., Walls, R., Wieczorek, J., Wilson, J., Zermoglio, P. F., & Simpson, A. (2019). Improving Darwin Core for research and management of alien species. *Biodiversity Information Science and Standards*, *3,* e38084. doi:10.3897/biss.3.38084

Guillera-Arroita, G., Lahoz-Monfort, J. J., Elith, J., Gordon, A., Kujala, H., Lentini, P. E., McCarthy, M. A., Tingley, R., & Wintle, B. A. (2015). Is my species distribution model fit for purpose? Matching data and models to applications: Matching distribution models to applications. *Global Ecology and Biogeography*, *24*(3), 276–292. doi:10.1111/geb.12268

Guisan, A., & Thuiller, W. (2005). Predicting species distribution: Offering more than simple habitat models. *Ecology Letters*, *8*(9), 993–1009. doi:10.1111/j.1461-0248.2005.00792.x

Guisan, A., Tingley, R., Baumgartner, J. B., Naujokaitis-Lewis, I., Sutcliffe, P. R., Tulloch, A. I. T., Regan, T. J., Brotons, L., McDonald-Madden, E., Mantyka-Pringle, C., Martin, T. G., Rhodes, J. R., Maggini, R., Setterfield, S. A., Elith, J., Schwartz, M. W., Wintle, B. A., Broennimann, O., Austin, M., … Buckley, Y. M. (2013). Predicting species distributions for conservation decisions. *Ecology Letters*, *16*(12), 1424–1435. doi:10.1111/ele.12189

Hawaii State Alien Species Coordinator. (2017, May 9). *Hawaii's Most Invasive Horticultural Plants*. http://www.hear.org/hortweeds/

Hijmans, R. J., Phillips, S., Leathwick, J., & Elith, J. (2020). *Dismo: Species Distribution Modeling. R package version 1.3-3*. https://CRAN.R-project.org/package=dismo

Hochachka, W. M., Fink, D., Hutchinson, R. A., Sheldon, D., Wong, W.-K., & Kelling, S. (2012). Data-intensive science applied to broad-scale citizen science. *Trends in Ecology & Evolution*, *27*(2), 130–137. doi:10.1016/j.tree.2011.11.006

Hochmair, H. H., Scheffrahn, R. H., Basille, M., & Boone, M. (2020). Evaluating the data quality of iNaturalist termite records. *PLOS ONE*, *15*(5), e0226534. doi:10.1371/journal.pone.0226534

Hughes, R. F., Asner, G. P., Litton, C. M., Selmants, P. C., Hawbaker, T. J., Jacobi, J. D., Giardina, C. P., & Sleeter, B. M. (2017). Influence of Invasive Species on Carbon Storage in Hawaiʻi's Ecosystems. In *Baseline and Projected Future Carbon Storage and Carbon Fluxes in Ecosystems of Hawaiʻi* (pp. 43–55).

Imada, C. (2012). *Hawaiian Native and Naturalized Vascular Plants Checklist* (Bishop Musem Technical Report 60). Bishop Museum.

Imada, C. (2019). *Hawaiian Naturalized Vascular Plants Checklist* (Bishop Musem Technical Report 69). Bishop Museum.

Isaac, N. J. B., Jarzyna, M. A., Keil, P., Dambly, L. I., Boersch-Supan, P. H., Browning, E., Freeman, S. N., Golding, N., Guillera-Arroita, G., Henrys, P. A., Jarvis, S., Lahoz-Monfort, J., Pagel, J., Pescott, O. L., Schmucki, R., Simmonds, E. G., & O'Hara, R. B. (2020). Data Integration for Large-Scale Models of Species Distributions. *Trends in Ecology & Evolution*, *35*(1), 56–67. doi:10.1016/j.tree.2019.08.006

Jacobi, J. D., Price, J. P., Fortini, L. B., M, G. I., Samuel, & Berkowitz, P. (2017). *Hawaii Land Cover and Habitat Status* [Data set]. U.S. Geological Survey. doi:10.5066/F7DB80B9

Johnson, B. A., Mader, A. D., Dasgupta, R., & Kumar, P. (2020). Citizen science and invasive alien species: An analysis of citizen science initiatives using information and communications technology (ICT) to collect invasive alien species observations. *Global Ecology and Conservation*, *21*, e00812. doi:10.1016/j.gecco.2019.e00812

Kadmon, R., Farber, O., & Danin, A. (2004). Effect of roadside bias on the accuracy of predictive maps produced by bioclimatic models. *Ecological Applications*, *14*(2), 401–413. doi:10.1890/02-5364

Kramer-Schadt, S., Niedballa, J., Pilgrim, J. D., Schröder, B., Lindenborn, J., Reinfelder, V., Stillfried, M., Heckmann, I., Scharf, A. K., Augeri, D. M., Cheyne, S. M., Hearn, A. J., Ross, J., Macdonald, D. W., Mathai, J., Eaton, J., Marshall, A. J., Semiadi, G., Rustam, R., … Wilting, A. (2013). The importance of correcting for sampling bias in MaxEnt species distribution models. *Diversity and Distributions*, *19*(11), 1366–1379. doi:10.1111/ddi.12096

Lehtiniemi, M., Outinen, O., & Puntila-Dodd, R. (2020). Citizen science provides added value in the monitoring for coastal non-indigenous species. *Journal of Environmental Management*, *267*, 110608. doi:10.1016/j.jenvman.2020.110608

Lewandowski, E., & Specht, H. (2015). Influence of volunteer and project characteristics on data quality of biological surveys: Data Quality of Volunteer Surveys. *Conservation Biology*, *29*(3), 713–723. doi:10.1111/cobi.12481

Liu, C., Berry, P. M., Dawson, T. P., & Pearson, R. G. (2005). Selecting thresholds of occurrence in the prediction of species distributions. *Ecography*, *28*(3), 385–393. doi:10.1111/j.0906-7590.2005.03957.x

Liu, C., Newell, G., & White, M. (2016). On the selection of thresholds for predicting species occurrence with presence-only data. *Ecology and Evolution*, *6*(1), 337–348. doi:10.1002/ece3.1878

Liu, C., White, M., & Newell, G. (2013). Selecting thresholds for the prediction of species occurrence with presence-only data. *Journal of Biogeography*, *40*(4), 778–789. doi:10.1111/jbi.12058

Mair, L., & Ruete, A. (2016). Explaining Spatial Variation in the Recording Effort of Citizen Science Data across Multiple Taxa. *PLOS ONE*, *11*(1), e0147796. doi:10.1371/journal.pone.0147796

Matteson, K. C., Taron, D. J., & Minor, E. S. (2012). Assessing Citizen Contributions to Butterfly Monitoring in Two Large Cities. *Conservation Biology*, *26*(3), 557–564. doi:10.1111/j.1523-1739.2012.01825.x

McCarthy, K. P., Fletcher Jr, R. J., Rota, C. T., & Hutto, R. L. (2012). Predicting species distributions from samples collected along roadsides: Road bias in predicting distributions. *Conservation Biology*, *26*(1), 68–77. doi:10.1111/j.1523-1739.2011.01754.x

McKinley, D. C., Miller-Rushing, A. J., Ballard, H. L., Bonney, R., Brown, H., Cook-Patton, S. C., Evans, D. M., French, R. A., Parrish, J. K., Phillips, T. B., Ryan, S. F., Shanley, L. A., Shirk, J. L., Stepenuck, K. F., Weltzin, J. F., Wiggins, A., Boyle, O. D., Briggs, R. D., Chapin, S. F., … Soukup, M. A. (2017). Citizen science can improve conservation science, natural resource management, and environmental protection. *Biological Conservation*, *208*, 15–28. doi:10.1016/j.biocon.2016.05.015

Merow, C., Smith, M. J., & Silander, J. A. (2013). A practical guide to MaxEnt for modeling species' distributions: What it does, and why inputs and settings matter. *Ecography*, *36*(10), 1058–1069. doi:10.1111/j.1600-0587.2013.07872.x

Meyer, C., Weigelt, P., & Kreft, H. (2016). Multidimensional biases, gaps and uncertainties in global plant occurrence information. *Ecology Letters*, *19*(8), 992–1006. doi:10.1111/ele.12624

Milanesi, P., Mori, E., & Menchetti, M. (2020). Observer-oriented approach improves species distribution models from citizen science data. *Ecology and Evolution*, *10*(21), 12104–12114. doi:10.1002/ece3.6832

Miller, D. A. W., Pacifici, K., Sanderlin, J. S., & Reich, B. J. (2019). The recent past and promising future for data integration methods to estimate species' distributions. *Methods in Ecology and Evolution*, *10*(1), 22–37. doi:10.1111/2041-210X.13110

Minden, V., Jacobi, J. D., Porembski, S., & Boehmer, H. J. (2010). Effects of invasive alien kahili ginger (*Hedychium gardnerianum*) on native plant species regeneration in a Hawaiian rainforest. *Applied Vegetation Science*, *13*(1), 5–14. doi:10.1111/j.1654-109X.2009.01056.x

Muscarella, R., Galante, P. J., Soley-Guardia, M., Boria, R. A., Kass, J. M., Uriarte, M., & Anderson, R. P. (2014). ENMeval: An R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models. *Methods in Ecology and Evolution*, *5*(11), 1198–1205. doi:10.1111/2041-210X.12261

Myers, N., Mittermeier, R. A., Mittermeier, C. G., da Fonseca, G. A. B., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, *403*(6772), 853–858. doi:10.1038/35002501

Newbold, T. (2010). Applications and limitations of museum data for conservation and ecology, with particular attention to species distribution models. *Progress in Physical Geography: Earth and Environment*, *34*(1), 3–22. doi:10.1177/0309133309355630

Niemiec, R. M., Ardoin, N. M., Wharton, C. B., & Brewer, F. K. (2017). Civic and natural place attachment as correlates of resident invasive species control behavior in Hawaii. *Biological Conservation*, *209*, 415–422. doi:10.1016/j.biocon.2017.02.036

Pacifici, K., Reich, B. J., Miller, D. A. W., Gardner, B., Stauffer, G., Singh, S., McKerrow, A., & Collazo, J. A. (2017). Integrating multiple data sources in species distribution modeling: A framework for data fusion*. *Ecology, 98*(3), 840–850. doi:10.1002/ecy.1710

Pauchard, A., Kueffer, C., Dietz, H., Daehler, C. C., Alexander, J., Edwards, P. J., Arévalo, J. R., Cavieres, L. A., Guisan, A., Haider, S., Jakobs, G., McDougall, K., Millar, C. I., Naylor, B. J., Parks, C. G., Rew, L. J., & Seipel, T. (2009). Ain't no mountain high enough: Plant invasions reaching new elevations. *Frontiers in Ecology and the Environment*, *7*(9), 479–486. doi:10.1890/080072

Paulay, G. (1994). Biodiversity on Oceanic Islands: Its Origin and Extinction. *American Zoologist*, *34*(1), 134–144. doi:10.1093/icb/34.1.134

Pettorelli, N. (2013). *The normalized difference vegetation index* (First edition). Oxford University Press.

Phillips, S. J. (2017). *A Brief Tutorial on Maxent*. http://biodiversityinformatics.amnh.org/open_source/maxent/

Phillips, S. J., Dudík, M., Elith, J., Graham, C. H., Lehmann, A., Leathwick, J., & Ferrier, S. (2009). Sample selection bias and presence-only distribution models: Implications for background and pseudo-absence data. *Ecological Applications*, *19*(1), 181–197. doi:10.1890/07-2153.1

Reaser, J. K., Simpson, A., Guala, G. F., Morisette, J. T., & Fuller, P. (2020). Envisioning a national invasive species information framework. *Biological Invasions, 22*(1), 21–36. doi:10.1007/s10530-019-02141-3

Richardson, D. M., & Pyšek, P. (2006). Plant invasions: Merging the concepts of species invasiveness and community invasibility. *Progress in Physical Geography: Earth and Environment*, *30*(3), 409–431. doi:10.1191/0309133306pp490pr

Richardson, D. M., & Whittaker, R. J. (2010). Conservation biogeography: Foundations, concepts and challenges. *Diversity and Distributions*, *16*(3), 313–320. doi:10.1111/j.1472-4642.2010.00660.x

Riesch, H., & Potter, C. (2014). Citizen science as seen by scientists: Methodological, epistemological and ethical dimensions. *Public Understanding of Science*, *23*(1), 107–120. doi:10.1177/0963662513497324

Robinson, O. J., Ruiz-Gutierrez, V., & Fink, D. (2018). Correcting for bias in distribution modelling for rare species using citizen science data. *Diversity and Distributions*, *24*(4), 460–472. doi:10.1111/ddi.12698

Robinson, O. J., Ruiz-Gutierrez, Viviana., Reynolds, M. D., Golet, G. H., Strimas-Mackey, M., & Fink, D. (2020). Integrating citizen science data with expert surveys increases accuracy and spatial extent of species distribution models. *Diversity and Distributions*, *26*(8), 976–986. doi:10.1111/ddi.13068

Rödder, D., & Engler, J. O. (2011). Quantitative metrics of overlaps in Grinnellian niches: Advances and possible drawbacks. *Global Ecology and Biogeography*, *20*(6), 915–927. doi:10.1111/j.1466-8238.2011.00659.x

Roman, L. A., Scharenbroch, B. C., Östberg, J. P. A., Mueller, L. S., Henning, J. G., Koeser, A. K., Sanders, J. R., Betz, D. R., & Jordan, R. C. (2017). Data quality in citizen science urban tree inventories. *Urban Forestry & Urban Greening*, *22*, 124–135. doi:10.1016/j.ufug.2017.02.001

Smith, C. W. (1985). Impact of alien plants on Hawaii's native biota. In *Hawaii's Terrestrial Ecosystems: Preservation and Management* (p. 72). Cooperative National Park Resources Studies Unit, University of Hawaii.

Srivastava, V., Lafond, V., & Griess, V. C. (2019). Species distribution models (SDM): applications, benefits and challenges in invasive species management. *CABI Reviews*, (2019), 1-13. doi:10.1079/PAVSNNR201914020

Steen, V. A., Elphick, C. S., & Tingley, M. W. (2019). An evaluation of stringent filtering to improve species distribution models from citizen science data. *Diversity and Distributions*, *25*(12), 1857–1869. doi:10.1111/ddi.12985

Steen, V. A., Tingley, M. W., Paton, P. W. C., & Elphick, C. S. (2021). Spatial thinning and class balancing: Key choices lead to variation in the performance of species distribution models with citizen science data. *Methods in Ecology and Evolution*, *12*(2), 216–226. doi:10.1111/2041-210X.13525

Steger, C., Butt, B., & Hooten, M. B. (2017). Safari Science: Assessing the reliability of citizen science data for wildlife surveys. *Journal of Applied Ecology*, *54*(6), 2053–2062. doi:10.1111/1365-2664.12921

Stolar, J., & Nielsen, S. E. (2015). Accounting for spatially biased sampling effort in presence-only species distribution modelling. *Diversity and Distributions*, *21*(5), 595–608. doi:10.1111/ddi.12279

Syfert, M. M., Smith, M. J., & Coomes, D. A. (2013). The effects of sampling bias and model complexity on the predictive performance of MaxEnt species distribution models. *PLoS ONE*, *8*(2), e55158. doi:10.1371/journal.pone.0055158

Tanner, A. M., Tanner, E. P., Papeş, M., Fuhlendorf, S. D., Elmore, R. D., & Davis, C. A. (2020). Using aerial surveys and citizen science to create species distribution models for an imperiled grouse. *Biodiversity and Conservation*, *29*(3), 967–986. doi:10.1007/s10531-019-01921-6

Theobald, E. J., Ettinger, A. K., Burgess, H. K., DeBey, L. B., Schmidt, N. R., Froehlich, H. E., Wagner, C., HilleRisLambers, J., Tewksbury, J., Harsch, M. A., & Parrish, J. K. (2015). Global change and local solutions: Tapping the unrealized potential of citizen science for biodiversity research. *Biological Conservation*, *181*, 236–244. doi:10.1016/j.biocon.2014.10.021

Tulloch, A. I. T., Mustin, K., Possingham, H. P., Szabo, J. K., & Wilson, K. A. (2013). To boldly go where no volunteer has gone before: Predicting volunteer activity to prioritize surveys at the landscape scale. *Diversity and Distributions*, *19*(4), 465–480. doi:10.1111/j.1472-4642.2012.00947.x

U.S. Department of Agriculture, Natural Resources Conservation Service. (2020). *Soil Survey Geographic (SSURGO) database*. https://websoilsurvey.sc.egov.usda.gov/

U.S. Geological Survey Gap Analysis Project. (2018). *Protected Areas Database of the United States (PAD-US): U.S. Geological Survey data release*. U.S. Geological Survey. doi:10.5066/P955KPLE

van Strien, A. J., van Swaay, C. A. M., & Termaat, T. (2013). Opportunistic citizen science data of animal species produce reliable estimates of distribution trends if analysed with occupancy models. *Journal of Applied Ecology*, *50*(6), 1450–1458. doi:10.1111/1365-2664.12158

Varela, S., Anderson, R. P., García-Valdés, R., & Fernández-González, F. (2014). Environmental filters reduce the effects of sampling bias and improve predictions of ecological niche models. *Ecography*. doi:10.1111/j.1600-0587.2013.00441.x

Vorsino, A. E., Fortini, L. B., Amidon, F. A., Miller, S. E., Jacobi, J. D., Price, J. P., Gon, S. 'Ohukani'ohi'a, & Koob, G. A. (2014). Modeling Hawaiian Ecosystem Degradation due to Invasive Plants under Current and Future Climates. *PLoS ONE*, *9*(5), e95427. doi:10.1371/journal.pone.0095427

Wagner, W. L., Herbst, D. R., & Sohmer, S. H. (1999). *Manual of the flowering plants of Hawai'i* (Rev. ed). University of Hawai'i Press : Bishop Museum Press.

Wallace, R. D., Bargeron, C. T., & Reaser, J. K. (2020). Enabling decisions that make a difference: Guidance for improving access to and analysis of invasive species information. *Biological Invasions*, *22*(1), 37–45. doi:10.1007/s10530-019-02142-2

Warner, K. D., & Kinslow, F. (2013). Manipulating risk communication: Value predispositions shape public understandings of invasive species science in Hawaii. *Public Understanding of Science*, *22*(2), 203–218. doi:10.1177/0963662511403983

Warren, D. L., Glor, R. E., & Turelli, M. (2008). Environmental niche equivalency versus conservatism: Quantitative approaches to niche evolution. *Evolution*, *62*(11), 2868–2883. doi:10.1111/j.1558-5646.2008.00482.x

Wilson, J. S., Pan, A. D., General, D. E. M., & Koch, J. B. (2020). More eyes on the prize: An observation of a very rare, threatened species of Philippine Bumble bee, Bombus irisanensis, on iNaturalist and the importance of citizen science in conservation biology. *Journal of Insect Conservation*, *24*(4), 727–729. doi:10.1007/s10841-020-00233-3

Zapponi, L., Cini, A., Bardiani, M., Hardersen, S., Maura, M., Maurizi, E., Redolfi De Zan, L., Audisio, P., Bologna, M. A., Carpaneto, G. M., Roversi, P. F., Sabbatini Peverieri, G., Mason, F., & Campanaro, A. (2017). Citizen science data as an efficient tool for mapping protected saproxylic beetles. *Biological Conservation*, *208*, 139–145. doi:10.1016/j.biocon.2016.04.035

Chapter 4. Landsat NDVI time series capture greening trends in Hawaiian dry forests

Supplementary materials for this chapter are provided in Appendix C.

Abstract

Tropical dry forests are highly threatened and fragmented in the Hawaiian Islands, and restoration requires intensive, active management and long-term monitoring. Remote sensing imagery has the potential to improve the consistency and longevity of ecosystem monitoring. We used a 1999-2022 Landsat time series of the Normalized Difference Vegetation Index (NDVI) to examine whether site-level trends in Hawaiian dry forest reflect the browning patterns observed at coarser spatial scales in the region. NDVI trends in active dry forest restoration sites were examined in order to test the utility of Landsat-resolution imagery in restoration monitoring. As dry forest is strongly influenced by rainfall and vegetation productivity has been previously linked to drying trends in Hawaii, we also compared NDVI trends to precipitation anomalies calculated from the Rainfall Atlas of Hawaii. Trends in median NDVI and robust coefficient of variation of NDVI were estimated in Hawaii's dry and wet seasons, and breakpoint analysis was used to detect trend departures. We found that median NDVI increased significantly in native and non-native dry forest sites. Greening occurred in spite of declines in rainfall and a positive correlation between median NDVI and precipitation anomalies, but was less common in non-native grasslands. Two well-established restoration sites, Auwahi and Makauwahi, have experienced significant increases in median NDVI, and seasonal variation in NDVI at Makauwahi has significantly declined. Breakpoints in NDVI trends coincided with the start of restoration at Makauwahi. These results demonstrate that, given adequate spatial scale and

establishment time, freely accessible, global Landsat imagery has the potential to enhance monitoring in dry forest restoration sites. They also highlight the need for site-level remote sensing imagery for more accurate estimation of vegetation trends in heterogeneous landscapes.

4.1. Introduction

Tropical dry forests are highly threatened ecosystems that continue to experience high rates of cover loss worldwide (Hansen et al., 2013; Murphy & Lugo, 1986; Sanchez-Azofeifa et al., 2005), yet they are under-protected and under-studied compared to temperate and tropical rainforests (Hoekstra et al., 2004; Quesada et al., 2009; Sunderland et al., 2015). In the Hawaiian Islands, over 25% of endangered plants are dry forest or dry scrub species (Cabin et al., 2000), and it is estimated that 90% of the region's original dry forest has been lost since the arrival of humans (Falk et al., 1996). Ongoing sources of disturbance include fire, feral ungulate activity, and non-native plant dispersal (Stone et al., 1992). Invasive pasture grasses have significantly altered Hawaii's natural fire regime, further reducing the cover of native species that are not adapted to increased fire intensity and frequency (Ellsworth et al., 2014). This has resulted in a patchwork of highly flammable grasslands and small, isolated dry forest fragments that are highly likely to experience further fragmentation (Balzotti et al., 2020; Cabin et al., 2000; Friday et al., 2015).

Advancements in the accessibility and processing of remote sensing data can be utilized to expand ecosystem monitoring over greater spatial and temporal scales (Secades et al., 2014). Satellite-derived vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), have long been used to evaluate vegetation health and change (Xue & Su, 2017). Global and large-scale regional studies have used time series of NDVI and other indices to demonstrate the varying, often region-specific responses of vegetation greenness to long-term climatic trends, including increases driven by warming and CO_2 fertilization (Xu et al., 2020; Zhu et al., 2016) and decreases due to drought or declines in rainfall (Hilker et al., 2014; Zhou et al., 2014). The Hawaiian Islands have experienced significant warming and drying trends during the last century (Frazier & Giambelluca, 2017; McKenzie et al., 2019), and two recent remote sensing studies have found associations between drier climate conditions and declines in forest productivity. Barbosa & Asner (2016) showed that drying has driven a decrease in forest greenness (using Enhanced Vegetation Index anomalies) in mesic to wet zones on the island of Hawaiʻi from 2002 to 2016, with particularly strong declines in photosynthetic activity and canopy volume on the drier, leeward side. Madson et al. (2022) examined monthly NDVI time series and found significant browning in both native and non-native vegetation across the archipelago from 1984 to 2019, and evidence of higher sensitivity to drought in leeward areas (Madson et al. 2022).

Remote sensing may also be used to improve the longevity and efficiency of conventional in situ restoration monitoring (de Almeida et al., 2020; Friday et al., 2015; Hausner et al., 2018; Reis et al., 2019). Studies in tidal marsh (Tuxen et al., 2008), grassland (Zhang et al., 2012), lagoon (Kim et al., 2015), and riparian (Sun et al., 2011) ecosystems have shown that NDVI can be used to monitor various post-restoration changes in vegetation cover and plant productivity. This particular application of remote sensing is an important area of research in Hawaiian dry forest management (Cordell et al., 2017; Friday et al., 2015). In Hawaii, dry forest conservation requires intensive restoration—e.g. ungulate exclusion, invasive grass control, supplemental irrigation, native species reintroduction and outplanting, etc. (Ammondt et al., 2013; Cabin et al., 2002; Ellsworth et al., 2015)—as well as sufficient monitoring (Holl, 2017; Stanturf et al., 2014). Regular evaluation at intermediate intervals provides data that can guide potential remediation and adaptive management (Dey & Schweitzer, 2014; Suding, 2011; Tuxen et al., 2008), while overall longer monitoring periods are needed to avoid misleading, short-term results (Herrick et al., 2006; Menges, 2008). Certain indicators of recovery, such as self-recruitment by introduced native plant material (Drayton & Primack, 2012), may progress at slower rates that cannot be adequately captured in shorter monitoring time frames, and others may not follow a linear trajectory (Matthews et al., 2009). The active restoration literature indicates that monitoring is generally insufficient, due in part to perceived costliness, unclear objectives or criteria for success, and limited time, resources, or expertise (Dey & Schweitzer, 2014; Stanturf et al., 2014; Suding, 2011). Though a few long-term examples have been shared in the literature (Faucette et al., 2008; Medeiros et al., 2014), a review of dry forest active restoration publications found that studies in Hawaii have been monitored for an average of three years (Dimson & Gillespie, 2020).

To our knowledge, a site-level remote sensing time series analysis has not been conducted in Hawaiian dry forest. The previously mentioned studies in Hawaii used 500-meter resolution Moderate Resolution Imaging Spectroradiometer (MODIS) and 0.05-degree (~5 kilometer) Advanced Very High Resolution Radiometer (AVHRR) data to detect negative trends in vegetation indices (J. M. Barbosa & Asner, 2016; Madson et al., 2022). But it is important to measure patterns across multiple spatial scales; remote sensing metrics can be highly influenced by pixel size, and there is often a mismatch between the spatial scale of imagery and the processes being monitored on the ground (Anderson, 2018).

We thus used a 23-year Landsat time series to examine dry forest NDVI trends in Hawaii, where small dry forests remnants are isolated over a heterogeneous landscape. Landsat imagery can be freely accessed through multiple platforms, and its 30-meter spatial resolution permits monitoring at the site-level. Though Landsat has a less frequent revisit interval of 16 days, it may be able to capture spatial trends that are obscured in coarser imagery. We estimated NDVI trends in native species-dominated and non-native species-dominated dry forest sites to investigate whether the browning trends detected elsewhere in Hawaii are also occurring in remaining dry forests. We examined the relationship between NDVI and rainfall anomaly trends, given recent drying trends in the state (Frazier & Giambelluca, 2017) and the strong influence of precipitation on tropical dry forest NDVI (Pau et al., 2010). We expected that NDVI and rainfall would be positively associated. Finally, we tested the utility of Landsat in detecting vegetation changes at active dry forest restoration sites, where non-native grasses were previously dominant and woody non-native species also occurred. We therefore estimated NDVI trends in non-native grassland sites as well. We hypothesized that, pre-restoration, typical NDVI values and NDVI seasonality would be similar to that of non-native grassland. At sites where native vegetation recovery was reported, post-restoration NDVI was expected to increase, become less variable, and approach values characteristic of dry forest.

This research examined three questions: 1) How have seasonal NDVI parameters changed in native Hawaiian dry forests from 1999 to 2022? 2) Are seasonal changes in NDVI associated with precipitation anomalies?; and 3) Do trends in Landsat-derived NDVI reflect reported changes in vegetation at dry forest restoration sites?

4.2. Methods

4.2.1. Native dry forest sites

Native Hawaiian dry forests are extremely rare, fragmented, and limited in extent. We identified nine native dry forest plots on Hawai‘i, Kaua‘i, Lana‘i, and Maui (Gillespie et al., 2011) and O‘ahu (Knight and Barton, 2012, unpublished data) using OpenNahele, a community-level forest plot database for the Hawaiian Islands (Craven et al., 2018). We selected plots with an area of ≥ 1000 m^2 in which a minimum of 80% of inventoried plants were native species and at least 30 total plants were inventoried. For each site, a 3x3 Landsat pixel window centered on the point location provided in OpenNahele was included in analysis.

4.2.2. Restoration sites

We identified four dry forest restoration sites—Auwahi, Makauwahi, Keaau, and Ohikilolo—greater than the area of a single Landsat pixel (≥ 0.1 hectare). A pixel was included in analysis if the majority (>50%) of its footprint was located inside the restored area.

Auwahi forest is located on private ranch land on the leeward side of Maui. The native understory was degraded by 19th-century grazing and burning practices and became densely covered by kikuyu grass (*Cenchrus clandestinus*) by the mid-20th century (see Medeiros et al., 2014 for site history). Restoration of a 4-hectare plot began in 1997 and included the construction of a perimeter fence to exclude feral ungulates, mass outplanting of *Dodonaea viscosa* and other natives, and two herbicide treatments spaced several months apart (1.5% glyphosate). Treated kikuyu mats were left on site. By 2012, native plant cover had increased by 57.6%. Since then, several thousand additional native plants have been planted, with ongoing minimal weed management (hand pulling and occasional herbicide application) (Erica von Allmen, *personal communication*).

Makauwahi Cave is a non-profit coastal reserve in Kauaʻi. Prior to restoration, the property supported few native species and was dominated by invasive species, including guinea grass (*Urochloa maxima)* and the small woody tree *Leucaena leucocephala* (see Burney & Burney, 2016 for site history). Restoration of an abandoned sugar cane field on the property began in 2005 with the reintroduction of 3,000 native and Polynesian outplants. Invasive vegetation control included hand removal and rotary tillage; no herbicides were used. Weeding took place from 2005 to 2010, after which it was required less frequently. Supplemental water was provided from 2005-2007 via drip irrigation for most of the site, then completely withdrawn in 2010. In 2012, a fence was constructed around most of the site to exclude feral pigs. Mean survival rate for tree and shrub species was 64.3% after 5 years, with most mortality occurring immediately after outplanting or withdrawal of supplemental irrigation.

Keaau and Lower Ohikilolo are located in the Waianae range of Oʻahu and managed by the Department of Forestry and Wildlife and the Oʻahu Army Natural Resources Program (OANRP). Lower Ohikilolo is highly fire-prone and dominated by invasive grasses (including guinea grass and *Melinis repens*), *L. leucocephala*, and various herbaceous non-natives (OANRP, 2022). A fence was constructed in 2000 to separate the area from a large goat population to the south, and invasive vegetation control began in 2001. Control currently occurs on a quarterly basis and emphasizes fuel load reduction by targeting invasive grasses through a combination of weed whacking and occasional post-emergent herbicide applications. Periodic outplanting of rare and common native species began in 2014, and native shrub cover doubled in certain parts of Ohikilolo after just three years.

In 2014, the Keaau management unit was fenced after the discovery of endangered native plant species in the area (OANRP, 2020). Several invasive species are widespread on the rocky terrain, including guinea grass, *L. leucocephala*, and the shrub *Mesosphaerum pectinatum*. Regular weed management began in 2015 and entails hand removal, weed whacking, and pre-emergent herbicide applications along fences and trails. Areas within 50 meters of rare taxa are prioritized. Reintroductions of native species began in 2016, followed by a mass outplanting (500 outplants) of common natives in 2017. We limited analysis to areas of Keaau and Ohikilolo where outplanting has occurred.

4.2.3. Non-native vegetation classes

Native and restored dry forest sites were compared to non-native species-dominated dry forest (non-native dry forest) and non-native species-dominated dry grassland (non-native grassland). The potential extent of dry forest includes areas with mean annual temperature >17°C, mean annual precipitation of 250-2000 mm, and a potential evapotranspiration (PET) to precipitation ratio >1 (Murphy & Lugo, 1986). We used this definition and gridded temperature, precipitation, and PET data (Giambelluca et al., 2013, 2014) to estimate a climatic envelope for dry forest in Hawaii, from which the non-native study sites were selected (Figure 4.1).

The Carbon Assessment of Hawaii land cover map (Jacobi et al., 2017) was used to identify continuous areas (≥ 10 ha) of non-native grassland and non-native dry forest within the potential dry forest extent and elevation range of the native and restored sites (Appendix C, Figure C1). For each non-native vegetation class, we selected nine 3x3 Landsat pixel windows for analysis. At least two plots were located on each of Hawaii’s four largest islands (Hawai‘i, Maui, O‘ahu, and Kaua‘i).

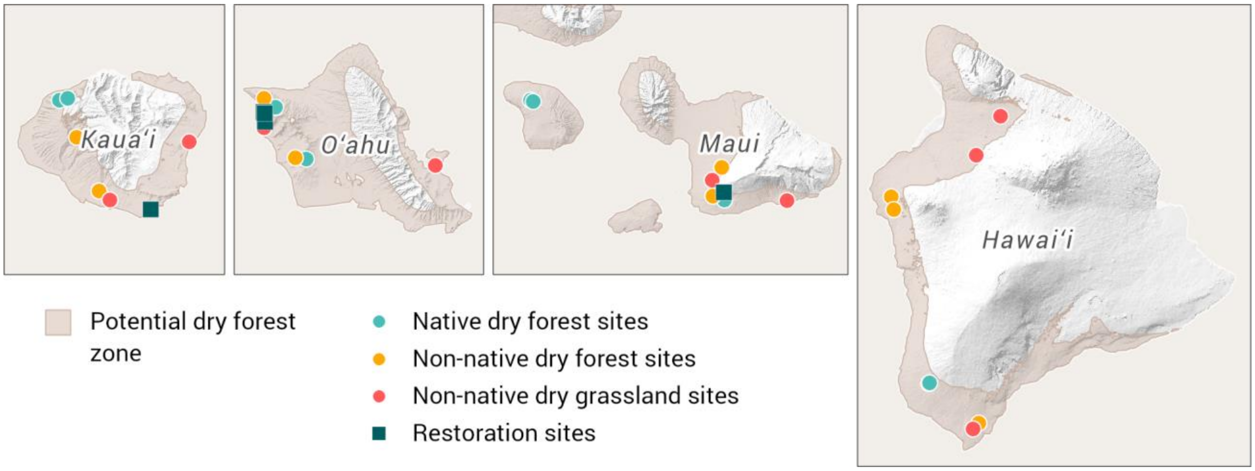

Figure 4.1
Study site locations and potential dry forest zone, defined using Murphy and Lugo (1986). Hillshade layer from State of Hawaii Office of Planning.

4.2.4. NDVI

NDVI is an indicator of vegetation productivity and photosynthetic capacity and is calculated as a difference ratio between red and near-infrared (NIR) reflectance [(NIR - Red) / (NIR + Red)], as chlorophyll absorbs visible light while the cell structure of healthy leaf tissue strongly reflects near-infrared light (Gamon et al., 1995; Pettorelli et al., 2005). Values range from +1 to -1, with negative values corresponding to clouds or water and higher values signifying denser vegetation and greater photosynthetic activity.

Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager (OLI), and Landsat 9 OLI Tier 1 collections were accessed through Google Earth Engine, a cloud computing platform that facilitates the processing and analysis of remote sensing data (Gorelick et al., 2017). We used the Collection 2, Level-2 surface reflectance product, which is atmospherically corrected and meets the solar zenith angle constraint of <76 degrees. NDVI values were computed from cloud-masked red and near-infrared bands, then extracted for the study pixels and exported for analysis. Only values greater than zero were retained, in order to reflect the typical NDVI of soil and vegetated surfaces (Roy et al., 2016). As consistent, clear Landsat 5 TM images were not available for the region, analysis utilized Landsat 7 ETM+, Landsat 8 OLI, and Landsat 9 OLI data only.

Landsat data spanned July 1999 to September 2022. Though individual Landsat sensors have a revisit interval of 16 days, temporal coverage was inconsistent, mainly due to cloud cover. The median number of image dates per pixel per year ranged from 1 (primarily in 1999) to 54 with a median of 9 (Table 4.1). NDVI observations were aggregated into seasonal time series of NDVI parameters. We aligned quarterly seasons—November-January (NDJ), February-April (FMA), May-July (MJJ), and August-October (ASO)—with Hawaii’s wet (November-April) and dry seasons (May-October) (Frazier & Giambelluca, 2017), and consequently excluded observations before August 1999 and after July 2022 from time series analysis.

NDVI parameters included median NDVI and robust coefficient of variation (RCV) of NDVI. We chose median rather than mean NDVI because the annual distribution of NDVI values was often moderately to highly skewed for most sites (Bulmer, 1979). RCV of NDVI is calculated by dividing the median absolute deviation by the median, and is a more suitable alternative to the mean-based coefficient of variation for skewed data (Arachchige et al., 2022). RCV provides a measure of seasonality and may capture the response of NDVI to climatic variations and other potential disturbances that cannot be detected by the median (H. A. Barbosa et al., 2006). A higher RCV signifies greater variability.

Table 4.1
Per study site, the number of Landsat pixels, number of unique Landsat image dates, and mean (± standard deviation) percentage of valid pixels (i.e. no cloud cover, NDVI > 0) per image date.

Class	Site	Island	# pixels	# image dates	% valid pixels
Native dry forest	Manuka-1	Hawaiʻi	9	166	89.8 ±22.8
	Manuka-2	Hawaiʻi	9	163	87.3 ±25.0
	Kokee-1	Kauaʻi	9	208	90.9 ±22.6
	Kokee-2	Kauaʻi	9	214	91.1 ±21.9
	Kanepuu-1	Lanaʻi	9	222	88.5 ±25.2
	Kanepuu-2	Lanaʻi	9	211	89.8 ±22.1
	Kanaio	Maui	9	325	91.3 ±21.5
	Nanakuli	Oʻahu	9	213	86.9 ±24.2
	Waianae	Oʻahu	9	165	87.3 ±24.9
Non-native dry forest	Kailua-1	Hawaiʻi	9	247	93.7 ±18.0
	Kalaoa	Hawaiʻi	9	216	90.6 ±21.7
	South Point-1	Hawaiʻi	9	404	92.7 ±19.6
	Hanapepe Valley	Kauaʻi	9	575	91.5 ±21.0
	Mokihana	Kauaʻi	9	243	91.9 ±21.0
	Kanaio Rd	Maui	9	245	88.3 ±25.8
	Keokea	Maui	9	233	90.7 ±22.7
	Kuaokala	Oʻahu	9	197	90.4 ±23.0
	Lualualei	Oʻahu	9	401	86.6 ±26.1

Non-native grassland	Pohakuloa	Hawaiʻi	9	372	94.2 ±17.4
	South Point-2	Hawaiʻi	9	411	92.3 ±19.5
	Waimea	Hawaiʻi	9	343	93.2 ±20.1
	Kalaheo	Kauaʻi	9	551	91.5 ±21.0
	Kapaa Bypass	Kauaʻi	9	567	92.4 ±19.7
	Kula Highway	Maui	9	222	89.5 ±23.6
	Piilani Highway	Maui	9	434	93.9 ±17.6
	Kailua-2	Oʻahu	9	293	90.9 ±21.3
	Makaha	Oʻahu	9	314	92.1 ±20.4
Restoration site	Makauwahi	Kauaʻi	14	775	85.7 ±27.4
	Auwahi	Maui	42	230	76.2 ±33.2
	Keaau	Oʻahu	5	257	81.6 ±25.7
	Ohikilolo	Oʻahu	10	345	71.4 ±28.9

4.2.5. NDVI analysis

To characterize general NDVI conditions in native dry forest, non-native dry forest, non-native grassland, and the four restoration sites, pixel-wise summaries of median NDVI and RCV of NDVI were calculated per season over the 1999-2022 study period. Pre- and post-restoration NDVI parameters were calculated for Makauwahi, Keaau, and Ohikilolo, using the year that native outplanting began as a threshold. NDVI parameters in the vegetation classes were also calculated for pre- and post-restoration periods for comparison. Kruskal-Wallis and post-hoc Wilcoxon rank sum tests were used to make pairwise comparisons and identify significant differences between groups.

NDVI trends in each vegetation class and restoration site were characterized by 1) estimating the slope and strength of potential monotonic trends within seasons, and 2) identifying potential breakpoints, i.e. changes within the full time series. Sen's slope estimator was used to evaluate trends in median NDVI and RCV of NDVI per season. The significance of the trend was determined using the Mann-Kendall test, a non-parametric test suitable for the detection of upward or downward monotonic trends in environmental data that may not necessarily be linear

(Hirsch et al., 1982; Kendall, 1975; Mann, 1945). Autocorrelation and partial autocorrelation functions were applied to time series of each vegetation class and restoration site; if serial correlation was observed, Mann-Kendall tests were used with the block bootstrap method to improve estimates of significance.

Though all study sites were located in the potential dry forest zone (Figure 4.1), mean elevation ranged from 7 to 1156 meters (mean 466 ±339) and annual rainfall from 650 to 1385 millimeters (mean 907 ±202). We therefore used Pearson's correlations to assess the relationship between site variables (mean elevation and mean annual rainfall) and median NDVI, RCV of NDVI, and the Kendall coefficient of each parameter over time.

Breakpoints signify shifts in a time series and divide it into segments. The Breaks for Additive Seasonal and Trend (BFAST) framework 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; Verbesselt, Hyndman, Newnham, et al., 2010; Xu et al., 2020). In this study, we tested the utility of BFAST in monitoring post-restoration changes in Landsat-derived NDVI parameters, and examined whether breakpoints in restoration time series coincided with changes in a site's management history, without concurrent breaks in climatically similar vegetation classes. The bfast() function in the R package 'bfast' was applied using a frequency of 4 and the harmonic seasonal model, which requires fewer observations and is less sensitive to short-term variations (Verbesselt, Hyndman, Zeileis, et al., 2010). We tested two minimum segment sizes of 0.08 and 0.13 (i.e. trend departures of at least 2 and 3 years, respectively). Overlap was determined using each breakpoint's 95% confidence interval.

4.2.6. Precipitation data and analysis

The relationship between NDVI and precipitation trends was examined using the Rainfall Atlas of Hawaii, a 250-meter resolution, gridded monthly and annual rainfall product that was recently expanded to span 1920-2019 (Giambelluca et al., 2013). Total rainfall was extracted using the center of each study site, and seasonal time series were created by summing monthly precipitation for the NDJ, FMA, MJJ, and ASO periods. We chose mean precipitation from 1978-2007 as a baseline as per Frazier and Giambelluca (2017). We then calculated the seasonal long-term precipitation anomaly (PA_t) and cumulative precipitation anomaly (CPA_t) as:

$$PA_t = \frac{\text{Precipitation}_t - \text{Precipitation}_{1978\text{-}2007}}{\text{Precipitation}_{1978\text{-}2007}}$$

$$CPA_t = PA_t + PA_{t-1}$$

PA_t is precipitation change in the year '*t*' relative to the baseline mean, calculated using $\textit{Precipitation}_t$ (total rainfall in the year '*t*') and $\textit{Precipitation}_{1978\text{-}2007}$ (mean precipitation of the 1978-2007 baseline period). CPA_t depicts the accumulation of relative changes in precipitation by summing PA in the year '*t*' and '*t-1*'. The significance of 1978-2019 seasonal precipitation trends at each study site were determined using Sen's slope estimator and the non-parametric Mann-Kendall test (Frazier & Giambelluca, 2017).

To evaluate the relationship between changes in seasonal rainfall and greenness from 1999 to 2019, correlation coefficients were calculated between PA_t and CPA_t and median and RCV of NDVI in each vegetation class and restoration site. As Shapiro-Wilk tests determined that PAt, CPAt, median NDVI, and RCV of NDVI were not normally distributed, we used the non-parametric Spearman rank correlation.

4.3. Results

4.3.1. NDVI by site and vegetation class

Wilcoxon rank sum tests found significant differences ($p < 0.05$) in native dry forest, non-native dry forest, and non-native grassland median NDVI over the 1999-2022 study period. Among these vegetation classes, median NDVI was highest in non-native dry forest and lowest in non-native grassland (Figure 4.2). It was significantly higher in the NDJ quarter than during the dry season (MJJ and ASO) ($p < 0.01$, Appendix C, Table C1). There was no statistical difference between RCV of NDVI of native and non-native dry forest sites, and RCV of NDVI was highest in non-native grassland in all seasons ($p < 0.001$). RCV peaked in the late dry season (ASO) and showed the most variation across quarters in non-native grassland.

Study site mean annual rainfall was positively associated with median NDVI and negatively associated RCV of NDVI in all three vegetation classes. This relationship was strongest for native dry forest ($r = 0.74$, $p < 0.001$; $r = -0.79$, $p < 0.001$). Mean elevation of native dry forest sites was also moderately positively correlated with median NDVI ($r = 0.47$, $p < 0.01$) and negatively correlated with RCV of NDVI ($r = -0.63$, $p < 0.001$). In the restoration site class, there was no correlation between site environment and NDVI parameters.

Pre- and post-restoration median NDVI was generally lower than that of native and non-native dry forest ($p < 0.05$), with a few exceptions where there was no statistical difference (Figure 4.2). Non-native grassland and pre- and post-restoration Ohikilolo median NDVI were statistically similar in all seasons. Keaau median NDVI was also similar to non-native grassland, except during FMA pre-restoration, when it was slightly higher. At Makauwahi, pre-restoration median NDVI was higher, lower, or similar to that of non-native grassland depending on the season, but after restoration, Makauwahi's median NDVI was consistently significantly higher (*p*

< 0.05). At Auwahi, median NDVI was similar to that of non-native grassland during the wet season (FMA and NDJ) and higher during the dry season (MJJ and ASO, $p < 0.001$).

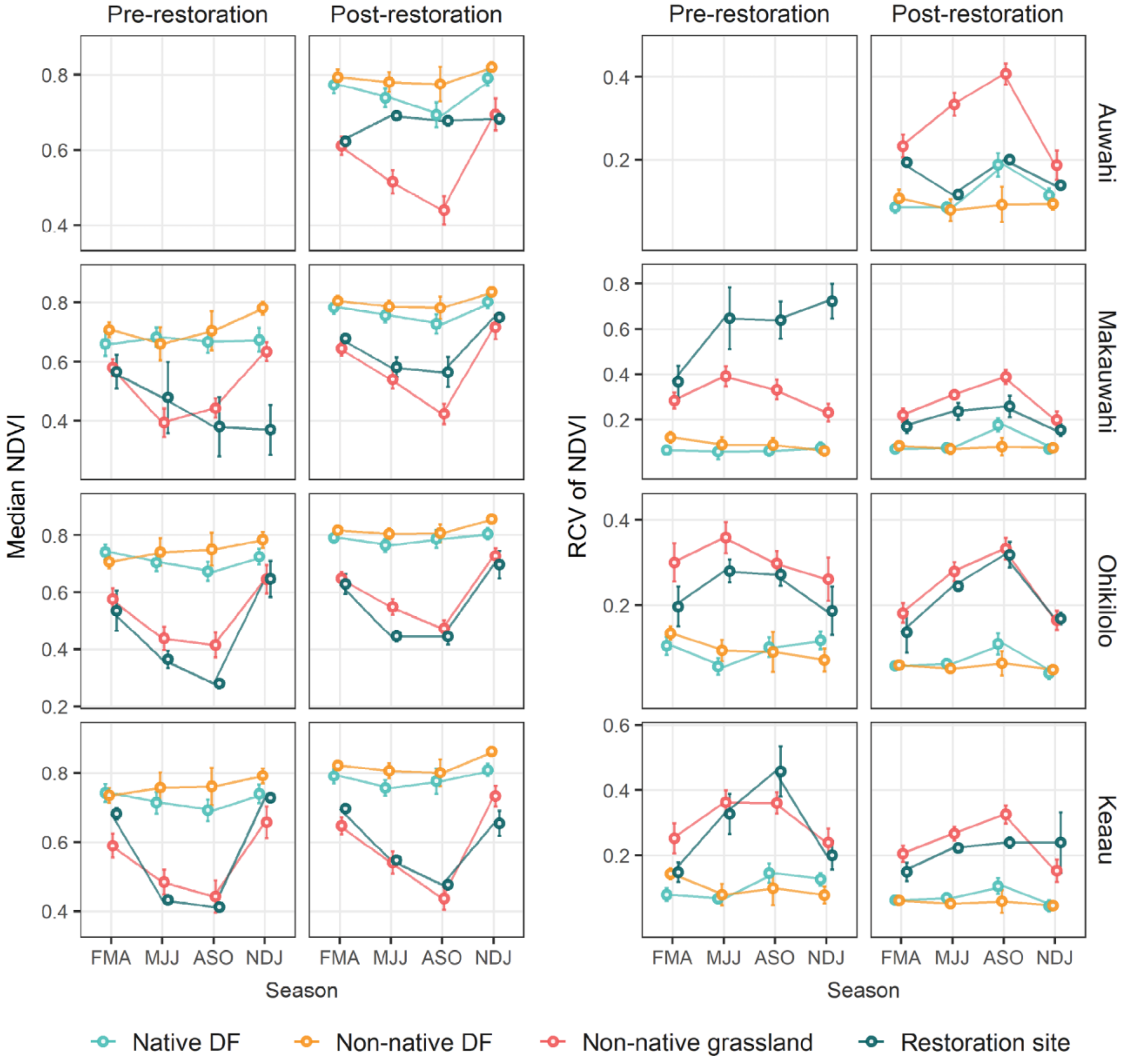

Figure 4.2
Pixel-wise NDVI parameters summarized within pre- and post-restoration periods (determined by the year that native outplanting began; Auwahi's post restoration period includes 1999-2022). Error bars show 95% confidence interval of the median. For significant differences between restoration sites before and after outplanting, see Appendix C, Table C2. 1999-2022 summary statistics for native dry forest (DF), non-native DF, and non-native grassland sites can be found in Appendix C, Table C3.

Pre- and post-restoration RCV of NDVI was significantly higher or statistically similar to that of native and non-native dry forest ($p < 0.05$). Compared to non-native grasslands, Auwahi and post-restoration Makauwahi had significantly lower RCV of NDVI ($p < 0.05$), while pre-restoration Makauwahi had higher RCV of NDVI in every season except FMA ($p < 0.001$). There was usually no statistical difference between RCV of NDVI in non-native grassland and pre- and post-restoration Keaau or Ohikilolo, wiith a few exceptions (Figure 4.2).

The clearest post-restoration shift in NDVI occurred at Makauwahi. After restoration, the site's median NDVI increased ($p < 0.05$) and RCV of NDVI decreased ($p < 0.001$) in all seasons, resulting in higher median NDVI and lower RCV of NDVI than non-native grassland (Figure 4.2; Appendix C, Table C2). Post-restoration changes at Keaau and Ohikilolo were similar in some ways, but less consistent. Keaau experienced significant increases in median NDVI during MJJ and NDJ ($p < 0.05$) as well as significant decreases in RCV of NDVI ($p < 0.05$) during the dry quarters (MJJ and ASO). At Ohikilolo, median NDVI increased significantly in FMA, MJJ, and ASO ($p < 0.05$), but RCV of NDVI increased during ASO ($p < 0.05$).

4.3.2. NDVI time series

Seasonal trends in median NDVI over time were primarily positive, and more common in forest classes than in non-native grassland (Figure 4.3). The strength and significance of the correlation varied by site and season, but the mean slope of each class did not differ significantly. Relatively high slopes were observed at Makauwahi and Auwahi. At Ohikilolo, a significant increase in median NDVI only occurred during the ASO quarter, while Keaau's median NDVI showed a significant negative trend during NDJ.

The slope of median NDVI was positively associated with site elevation ($r = 0.60$, $p < 0.001$) and negatively associated with site mean annual rainfall ($r = -0.34$, $p < 0.05$) in non-native dry forest. Otherwise, site environment was not correlated with changes in NDVI.

Aside from significant increases in RCV of NDVI at Makauwahi, the direction of the RCV of NDVI trend was more variable across sites and seasons (Figure 4.4). In the majority of cases, there was no strong association, though increases were more common in forest sites and decreases more common in grassland sites.

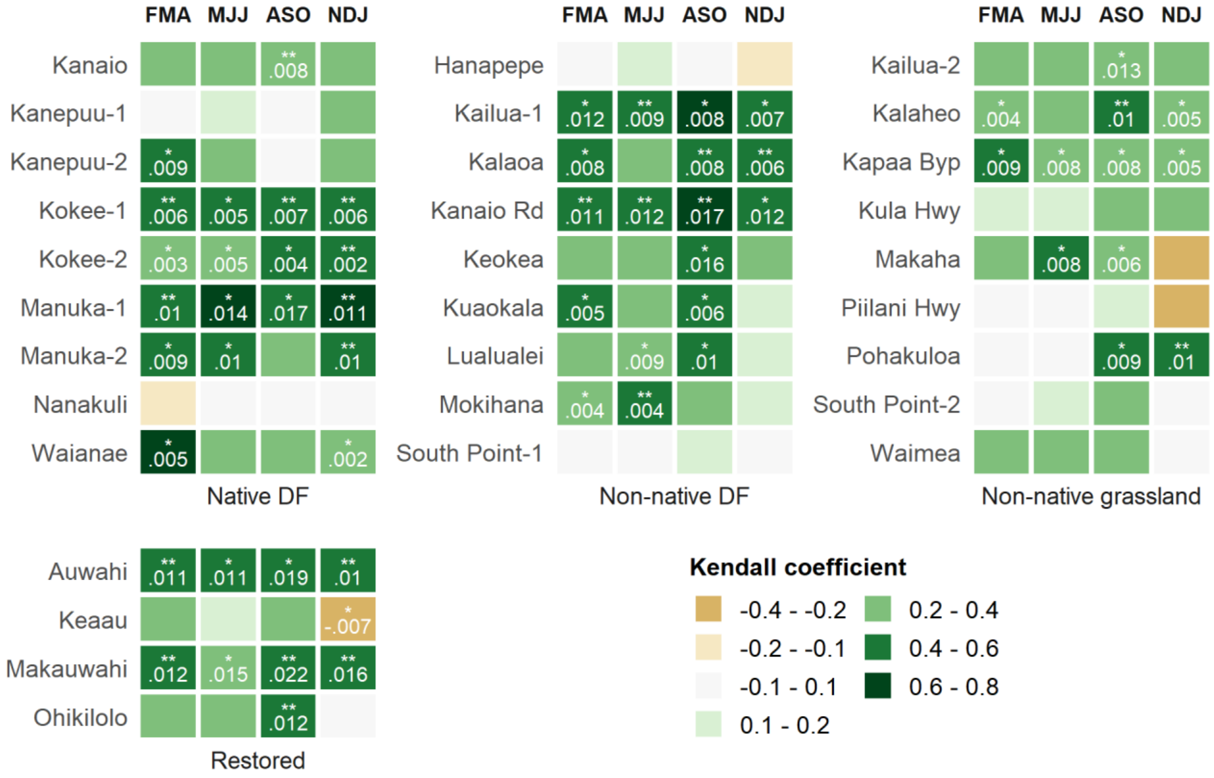

Figure 4.3

Correlation of seasonal median NDVI and year from 1999-2022 (*$p < 0.05$, **$p < 0.01$). Sens slope given for significant relationships. Brown and green tiles indicate a decrease or increase in median NDVI over time, respectively. DF = dry forest.

Breakpoints were detected in median NDVI and/or RCV of NDVI time series at each restoration site, as well as in median NDVI of native and non-native dry forest (Figure 4.5). Both breakpoints in median NDVI at Auwahi coincided with breakpoints in native dry forest, and the direction of the trend departures was similar. Median and RCV of NDVI breakpoints at Makauwahi had the clearest overlap with the site’s restoration start date. The 95% confidence interval of the Ohikilolo break, estimated to occur in 2005, was wide and overlapped a native dry forest breakpoint. Restoration at Keaau began after breaks detected in RCV of NDVI, which highlighted a steep rise in RCV between NDJ 2012 and MJJ 2014.

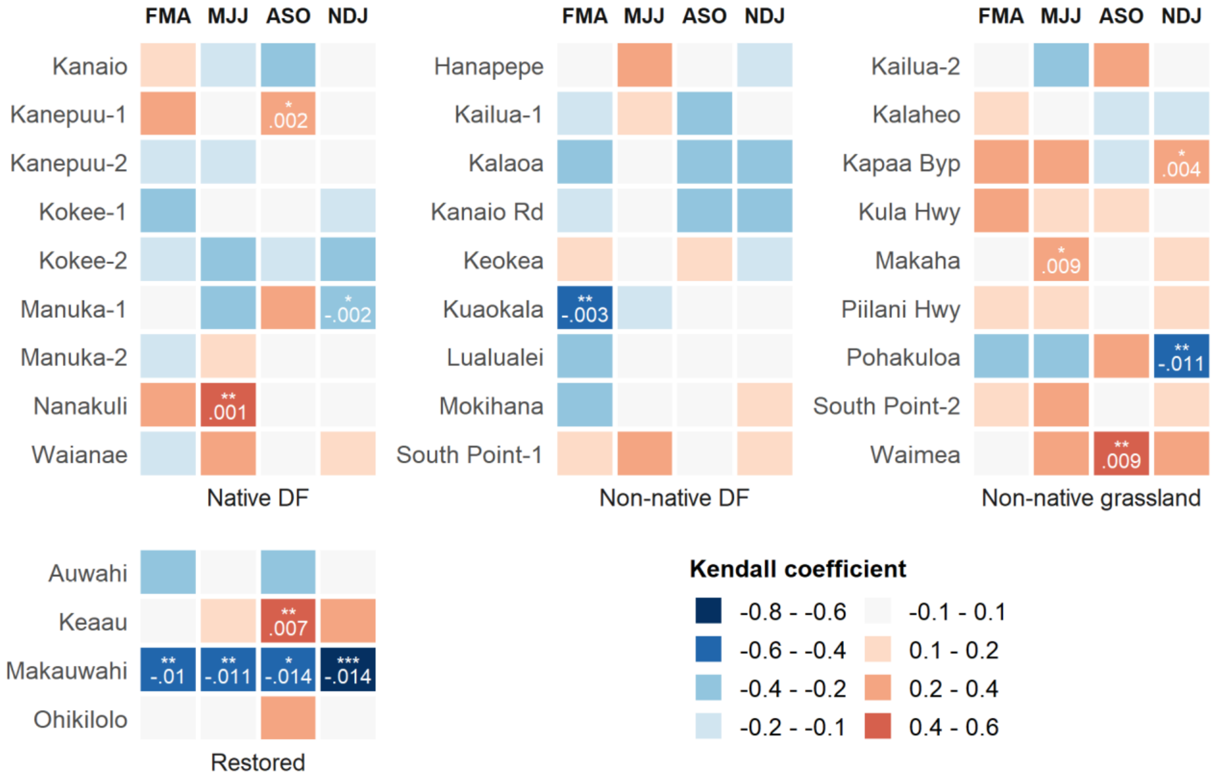

Figure 4.4

Correlation of seasonal RCV of NDVI and year from 1999-2022 (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$). Sens slope given for significant relationships. Blue and red tiles indicate a decrease or increase in RCV over time, respectively. DF = dry forest.

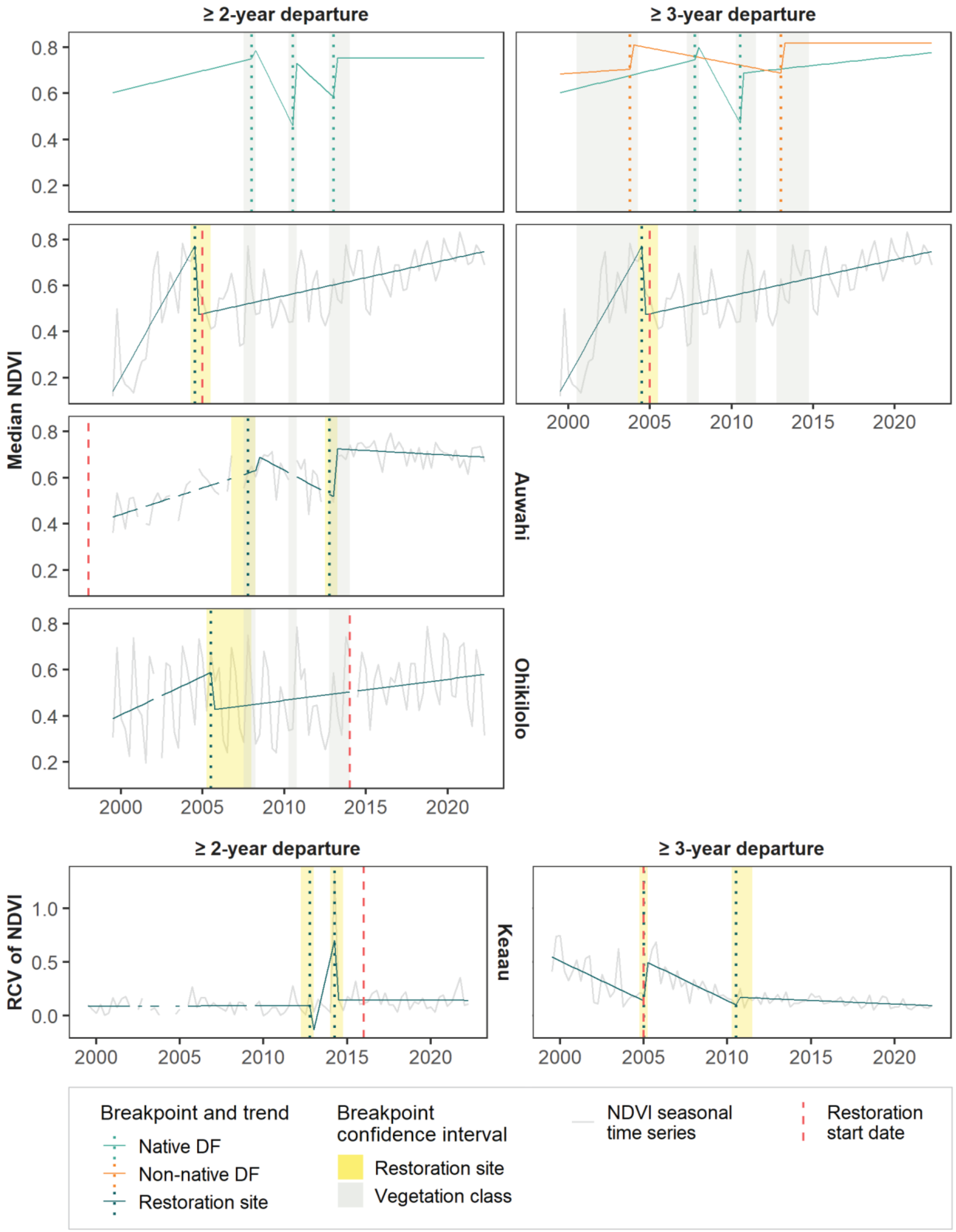

Figure 4.5

Significant breakpoints (dotted lines) and trends in median and RCV of NDVI time series indicated by BFAST, for minimum trend departure lengths of 2 and 3 years. Red dashed lines show initial outplanting dates at restoration sites. DF = dry forest.

4.3.3. Precipitation anomalies

Mann-Kendall tests indicated weak to moderate negative trends in the seasonal long-term precipitation anomaly (PA_t) and cumulative precipitation anomaly (CPA_t) from 1978 to 2019, and statistically significant trends at 11 out of 31 study sites (Appendix C, Table C4). Some positive trends occurred during the FMA, MJJ, and ASO quarters, but these were not significant and coefficients were low (mean $r = 0.07 \pm 0.05$). During the dry season, the PA_t and CPA_t trends were positively correlated with site elevation (MJJ CPA_t $r = 0.39$, $p < 0.05$; ASO CPA_t $r = 0.49$, $p < 0.01$; ASO PA_t $r = 0.43$, $p < 0.05$) and negatively correlated with site rainfall (MJJ PA_t $r = -0.37$, $p < 0.05$; ASO CPA_t $r = -0.39$, $p < 0.05$). During the NDJ quarter, PA_t coefficients were positively associated with site rainfall ($r = 0.40$, $p < 0.05$).

At the majority of study sites, seasonal PA_t and CPA_t were positively associated with median NDVI (Figure 4.6; Appendix C, Table C5). The strength and significance of the correlation were most consistent in non-native grassland sites and during the ASO quarter. Native and non-native dry forest study sites and the NDJ quarter in general showed more variation. The relationship between each seasonal precipitation anomaly and RCV of NDVI was primarily negative, but varied widely among study sites and seasons (Appendix C, Table C6). Trends were relatively weak, and statistical significance was observed for only a few sites.

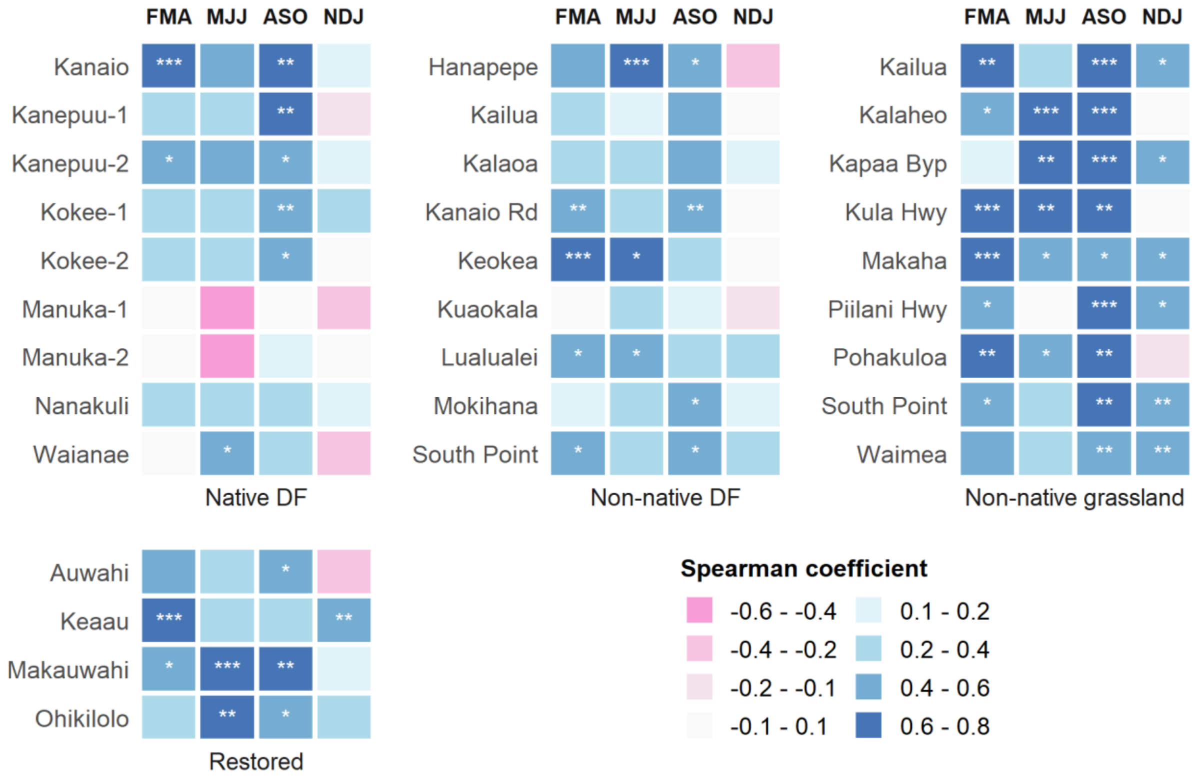

Figure 4.6
Spearman correlation of PA_t and median NDVI (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$) from 1999-2019. Pink and blue tiles indicate a negative or positive relationship, respectively. DF = dry forest.

4.4. Discussion

Native dry forest became greener over the study period, a finding that differs from previous studies in this region at coarser spatial scales. Increases in median NDVI occurred in spite of a positive correlation between site mean annual rainfall and median NDVI, and despite negative precipitation trends. Non-native grassland NDVI was most strongly associated with precipitation anomalies. Restoration sites also greened during this time period, especially the larger, more established sites of Makauwahi and Auwahi. At Makauwahi, significant breakpoints in both median NDVI and RCV of NDVI coincided with the start of restoration. Keaau and Ohikilolo were outplanted relatively recently and likely require additional time before restoration results can be detected at Landsat resolution.

4.4.1. NDVI in native dry forest

In the native dry forest plots in this study, vegetation greenness was lower and more variable at drier sites and during dry periods. We observed significantly higher median NDVI during the wet season (NDJ and FMA) compared to the dry season (MJJ and ASO). Native dry forest sites exhibited the strongest positive correlation between mean annual rainfall and median NDVI, with the highest median NDVI occurring at the wettest sites (Waianae and Nanakuli) and the lowest values occurring at the driest (Kanaio). Mean rainfall at native sites was also strongly negatively associated with RCV of NDVI, which was highest during the late dry season.

Native dry forests had lower median NDVI than non-native dry forests. The greatest difference occurred in the dry ASO quarter, during which native RCV of NDVI was also significantly higher. This is not unprecedented in Hawaiian rainforest: stands of invasive *Morella faya* exhibit higher NDVI than stands of the common native *Metrosideros polymorpha*, particularly during periods of lower rainfall (Asner et al., 2006). *M. polymorpha* has also shown more conservative growth and resource use than invasive tree species in wet environments (Cavaleri et al., 2014). Our results offer evidence that dry forests dominated by non-native species may also experience less stress during the peak dry season.

Over the last two decades, median NDVI showed significant, albeit low magnitude, increases at the majority of native and non-native dry forest sites in one or more seasons. Greening in tropical forest, due to factors such as elevated atmospheric CO2, has been observed in other regions (Xu et al., 2020; Zhu et al., 2016), but our Landsat results diverge from other studies in the Hawaiian Islands, which have attributed negative vegetation index trends to declines in precipitation and or worsening drought conditions (J. M. Barbosa & Asner, 2016; Madson et al., 2022). The MODIS-based analysis of Barbosa & Asner (2016) focused on mesic to wet forests, which may help to explain the difference in our results. While Madson et al. (2022) did not differentiate between forests and other vegetation types in their AVHRR analysis, they found significant browning in both native and non-native vegetation during every month but January. Forest NDVI trends are known to vary across datasets of different spatial resolutions (Arjasakusuma et al., 2018; Fensholt & Proud, 2012), and discrepancies between Landsat- and AVHRR-derived trends could be partially attributed to spatial aggregation of multiple vegetation types within larger pixels (Munyati & Mboweni, 2013). Dry forests, being fragmented, limited in distribution, and a small percentage of land cover on the main Hawaiian Islands (Jacobi et al., 2017), are unlikely to occupy the area of an AVHRR pixel. It is thus possible that a) native and non-native dry forests are exceptions to broader browning trends, b) our study sites occur in the AVHRR pixels in which Madson et al. (2022) found no significant change in NDVI, and so are not representative of broader trends that are indeed affecting dry forests. In native sites where greening was not observed (Kanepuu-1 and Nanakuli), significant trends in RCV of NDVI suggest that variation in dry season productivity has been increasing. Additional samples, and likely a longer time series, would be needed to explore these trends further.

The strength of the NDVI trends in this study is limited by the length and temporal resolution of the Landsat time series. Sparse coverage prior to 1999 truncated the time series, limiting detection of trends that might become more apparent over a longer observation period. The AVHRR analysis by Madson et al. (2022), for instance, spanned 1984 to 2019. Additionally, the Landsat spatial resolution allows us to capture site-level variations in NDVI, but its revisit interval required observations to be seasonally aggregated. Coupled with missing data values due to cloud cover, this could potentially bias median NDVI values and obscure seasonal site variations.

4.4.2. Precipitation trends and NDVI

Though only a few significant trends were detected, seasonal trends in both precipitation anomalies were primarily negative from 1978-2019. Across the Hawaiian Islands, dry season rainfall has declined more rapidly at locations above 1500 meters elevation (Frazier & Giambelluca, 2017). We found that the strength of the negative dry season PA_t and CPA_t trends was greater at lower elevations; however, all of the sites in this study were below 1200 meters, and may constitute an insufficient number of samples. We also observed weak but significant correlations between site mean annual rainfall and the precipitation anomaly trends in certain quarters, suggesting that drying trends have been relatively stronger at historically wetter sites during the dry season, and at drier sites during the wet season.

Warmer, drier conditions in the Hawaiian Islands have been previously associated with declines in NDVI (J. M. Barbosa & Asner, 2016). At the majority of study sites, median NDVI was positively correlated with precipitation anomalies in at least one season, usually ASO (Figure 4.6). Yet in spite of the overall downward trend in rainfall, median NDVI at 22 of 31 study sites increased significantly, depending on the season, over the last two decades. While it seems counterintuitive that sites should become greener while the climate is drying, the precipitation trends in Hawaii have not been consistent through time (Frazier & Giambelluca, 2017). The response of different vegetation types also varied somewhat. The class showing the fewest increases in median NDVI, non-native grassland (Figure 4.3), had the strongest and most consistent relationship with precipitation anomalies (Figure 4.6). Shallow-rooted invasive grasses like *Cenchrus setaceus* are opportunistic and able to exploit shallow water sources, but are less productive in the absence of rainfall events (Cordell & Sandquist, 2008). Native woody species have deeper root systems that can access soil water during the dry season (Calder & Dye, 2001), and also perhaps when anomalous dry periods occur. This may explain why native sites like Manuka-1 and Manuka-2 have become greener, despite being situated in a region of Hawaiʻi that has experienced the most significant drying trends (Frazier & Giambelluca, 2017).

Should rainfall in Hawaii continue to decline, non-native grasslands will become drier, and will likely exacerbate the risk of wildfire and loss of existing dry forest (Trauernicht, 2019). Hotter, drier conditions are also expected to reduce forest productivity, increase tree mortality rates, and impede recovery of native species (Allen et al., 2015; Anderson-Teixeira et al., 2013). The productivity of native and restored dry forests sites, amid anomalous declines in precipitation, is an encouraging testament to the value of restoration efforts and of dry forests themselves, though this is not to say that dry forests are invulnerable to extended periods of drought. The 2007-2011 departure from the positive trend in native dry forest median NDVI coincides with Hawaii's longest and most intense period of drought since 2000 (droughtmonitor.unl.edu). A concurrent trend was not detected in non-native dry forest, which may be less sensitive to dry periods (Asner et al., 2006). Further analysis of drought and other potential drivers is needed to understand the response of site greenness to long-term climate trends in Hawaii.

4.4.3. Post-restoration NDVI trends

Makauwahi experienced the most significant and apparent changes in NDVI parameters over the study period. Seasonal NDVI patterns at the site initially resembled those of non-native dry grassland, but greenness increased and became less variable after restoration activities began (Figure 4.2). These shifts were visible in the Makauwahi NDVI time series as well, which were positive for median NDVI and negative for RCV of NDVI (Figures 4.3-4.4). BFAST analysis detected breakpoints in NDVI trends that coincided with the restoration start date in 2005 (Figure

4.5): median NDVI briefly dropped, then increased, while RCV of NDVI rose, then decreased. Native dry forest greenness is significantly higher than non-native grassland, and seasonal and annual variation in NDVI is significantly lower. The breaks and trends at Makauwahi likely reflect the removal of non-native guinea grass and *L. leucocephala* and the subsequent, gradual establishment and unassisted recruitment of outplanted native species (Burney & Burney, 2016). A second breakpoint in RCV of NDVI occurred in 2010, after which the decline in RCV was more gradual. This may be another indication of native species progress at the site; Burney and Burney (2016) reported that by 2010, native plant size and dominance had increased to the point that less intense weeding was needed and all supplemental water was withdrawn.

Median NDVI at Auwahi, the most established of the restoration sites, experienced an approximately five-year departure from the positive trend from late 2007-2012 (Figure 4.5). These breakpoints coincided with those of native dry forest and the aforementioned period of prolonged drought, which was more severe on Maui and Hawaiʻi than on Kauaʻi and Oʻahu (droughtmonitor.unl.edu). Nonetheless, greenness has increased significantly at Auwahi since 1999, and NDVI is approaching values typical of native dry forest, particularly in the dry season. Though additional plantings have been conducted at the site since 2014, unassisted recruitment has also occurred for the majority of native woody species (Medeiros et al., 2014).

The management of Keaau and Ohikilolo sites differs from restoration of Auwahi and Makauwahi in several ways. Native outplanting began more recently, and has occurred in waves and in relatively smaller patches; the outplanted area at Keaau was the smallest in this study, and Ohikilolo’s outplanted areas are dispersed over a larger management unit (Oahu Army Natural Resources Program, 2020; Oʻahu Army Natural Resources Program, 2021). Removal of non-native vegetation, though extensive, has been performed more gradually and did not always consist of complete eradication. Results of these efforts may be more difficult to track at the Landsat resolution, making interpretation of the NDVI time series less straightforward.

Dry season median NDVI has increased at Ohikilolo, but seasonal variation in greenness has not much changed. Median NDVI values were still similar to non-native grassland, and no breakpoints were detected near or after the start of outplanting. Though OANRP surveys observed a significant increase in native shrub cover at the oldest outplanted area, the Ohikilolo plantings may need additional time before changes can be detected at a 30-meter spatial scale (Oʻahu Army Natural Resources Program, 2021). Furthermore, invasive *Myoporum* thrips were discovered at the site in 2020, which may affect the establishment of *Myoporum sandwicensis* outplants. One median NDVI breakpoint was identified in 2005, which had a relatively wide confidence interval (Figure 4.5). Several disturbance events occurred during the study period, including a 2003 fire in the northern region of the site, and fence breaches by feral goats multiple times from 2003-2008. Significant drying also occurred at the site during MJJ and NDJ (Appendix C, Table C4), but it is uncertain whether disturbance or climate factors influenced the trend departure.

Though pre- and post-restoration NDVI summaries for Keaau indicated that dry season RCV of NDVI has declined, Keaau was also one of six sites at which RCV of NDVI shows a significant positive monotonic trend. BFAST analysis indicated that this increase was steepest between 2012-2014 (Figure 4.5). These results are somewhat unsurprising, as outplanting did not begin until 2016 and the site burned in 2018. Recruitment by native species was observed after the fire, and outplanting has continued since then. Like Ohikilolo, continued monitoring of Keaau may reveal clearer post-restoration trends in NDVI.

4.4.4. Management implications

Trends at Makauwahi and Auwahi demonstrate the potential of Landsat NDVI time series to aid long-term restoration monitoring. The slopes of median NDVI at both sites, and of RCV at Makauwahi, were greater than those that occurred in native and non-native vegetation classes. Results at Makauwahi in particular highlight the utility of Landsat in capturing management-related breaks in greenness trends over a >20 year time series. In many regions, recovery of tropical dry forest is impeded by invasive grasses (Griscom & Ashton, 2011; Sanchez-Azofeifa et al., 2005). Landsat imagery, which is freely accessible and global in coverage, could provide a cost-effective, efficient means of extending restoration monitoring periods at a global scale where high resolution plot data are available.

One key shortcoming of the parameters used here is a limited ability to distinguish native species recovery from existing non-native woody vegetation. At Auwahi, for example, invasive *Bocconia frutescens* was common in restoration plots (Medeiros et al., 2014). While the transition from grassland to dry forest was more evident from the Landsat time series, hyperspectral band analysis at a finer spatial resolution would likely be needed to identify species-level differences (Somers & Asner, 2013).

4.5. Conclusion

Using a 1999-2022 Landsat time series, we examined seasonal NDVI trends in native dry forest, non-native dry forest, and non-native grassland, and monitored changes in productivity at dry forest restoration sites. We found significant increases in median NDVI in each vegetation class, but more often in the forest classes. Median NDVI was positively associated with precipitation anomalies, particularly in non-native grassland, but positive NDVI trends have occurred in dry forest despite long-term declines in precipitation, highlighting the ability of dry forest to remain productive when non-native grasslands are not. However, persistent dry conditions can have more substantial effects, as suggested by breaks in positive median NDVI trends in Auwahi and native dry forest, which coincided with a prolonged period of drought across the Hawaiian Islands. Further investigation of drought and other potential drivers is needed to better understand the relationship between NDVI and long-term climatic trends.

These results underscore the need for consistent and more accurate dry forest monitoring in Hawaii. Previous NDVI studies in the Hawaiian Islands have observed browning trends at coarser spatial scales (e.g. 500 m, 5 km), but finer resolution imagery is needed to differentiate trends in fragmented dry forest patches from the surrounding landscape. Our results also highlight the potential of site-level remote sensing to aid and extend restoration monitoring efforts. We observed significant greening trends at the larger and more established restoration sites, Makauwahi and Auwahi. At Makauwahi, NDVI increased and became more stable after restoration, and trend breakpoints coincided with the start of outplanting and other management actions. Trends were more variable at Keaau and Ohikilolo, where ouplanting began relatively more recently and several disturbance events have occurred. However, extended time series of Landsat or finer resolution imagery could facilitate long-term monitoring efforts at these sites.

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References

Allen, C. D., Breshears, D. D., & McDowell, N. G. (2015). On underestimation of global vulnerability to tree mortality and forest die-off from hotter drought in the Anthropocene. *Ecosphere*, *6*(8), art129. doi:10.1890/ES15-00203.1

Ammondt, S. A., Litton, C. M., Ellsworth, L. M., & Leary, J. K. (2013). Restoration of native plant communities in a Hawaiian dry lowland ecosystem dominated by the invasive grass *Megathyrsus maximus*. *Applied Vegetation Science*, *16*(1), 29–39. doi:10.1111/j.1654-109X.2012.01208.x

Anderson, C. B. (2018). Biodiversity monitoring, earth observations and the ecology of scale. *Ecology Letters*, *21*(10), 1572–1585. doi:10.1111/ele.13106

Anderson-Teixeira, K. J., Miller, A. D., Mohan, J. E., Hudiburg, T. W., Duval, B. D., & DeLucia, E. H. (2013). Altered dynamics of forest recovery under a changing climate. *Global Change Biology*, *19*(7), 2001–2021. doi:10.1111/gcb.12194

Arachchige, C. N. P. G., Prendergast, L. A., & Staudte, R. G. (2022). Robust analogs to the coefficient of variation. *Journal of Applied Statistics*, *49*(2), 268–290. doi:10.1080/02664763.2020.1808599

Arjasakusuma, S., Yamaguchi, Y., Nakaji, T., Kosugi, Y., Shamsuddin, S.-A., & Lion, M. (2018). Assessment of values and trends in coarse spatial resolution NDVI datasets in Southeast Asia landscapes. *European Journal of Remote Sensing*, *51*(1), 863–877. doi:10.1080/22797254.2018.1496799

Asner, G. P., Martin, R. E., Carlson, K. M., Rascher, U., & Vitousek, P. M. (2006). Vegetation–Climate Interactions among Native and Invasive Species in Hawaiian Rainforest. *Ecosystems*, *9*(7), 1106–1117. doi:10.1007/s10021-006-0124-z

Balzotti, C. S., Asner, G. P., Adkins, E. D., & Parsons, E. W. (2020). Spatial drivers of composition and connectivity across endangered tropical dry forests. *Journal of Applied Ecology*, *57*(8), 1593–1604. doi:10.1111/1365-2664.13632

Barbosa, H. A., Huete, A. R., & Baethgen, W. E. (2006). A 20-year study of NDVI variability over the Northeast Region of Brazil. *Journal of Arid Environments*, *67*(2), 288–307. doi:10.1016/j.jaridenv.2006.02.022

Barbosa, J. M., & Asner, G. P. (2016). Effects of long-term rainfall decline on the structure and functioning of Hawaiian forests. *Environmental Research Letters*, *12*(9), 094002. doi:10.1088/1748-9326/aa7ee4

Bulmer, M. G. (1979). *Principles of statistics*. Dover Publications.

Burney, D. A., & Burney, L. P. (2016). Monitoring results from a decade of native plant translocations at Makauwahi Cave Reserve, Kaua`i. *Plant Ecology*, *217*(2), 139–153. doi:10.1007/s11258-015-0535-z

Cabin, R. J., Weller, S. G., Lorence, D. H., Cordell, S., Hadway, L. J., Montgomery, R., Goo, D., & Urakami', A. (2002). Effects of Light, Alien Grass, and Native Species Additions on Hawaiian Dry Forest Restoration. *Ecological Applications*, *12*(6), 17.

Cabin, R. J., Weller, S. G., Lorence, D. H., Flynn, T. W., Sakai, A. K., Sandquist, D., & Hadway, L. J. (2000). Effects of Long-Term Ungulate Exclusion and Recent Alien Species Control on the Preservation and Restoration of a Hawaiian Tropical Dry Forest. *Conservation Biology*, *14*(2), 439–453. doi:10.1046/j.1523-1739.2000.99006.x

Calder, I., & Dye, P. (2001). Hydrological impacts of invasive alien plants. *Land Use and Water Resources Research*, *1*(7), 1–12.

Cavaleri, M. A., Ostertag, R., Cordell, S., & Sack, L. (2014). Native trees show conservative water use relative to invasive trees: Results from a removal experiment in a Hawaiian wet forest. *Conservation Physiology*, *2*(1), cou016–cou016. doi:10.1093/conphys/cou016

Cordell, S., Questad, E. J., Asner, G. P., Kinney, K. M., Thaxton, J. M., Uowolo, A., Brooks, S., & Chynoweth, M. W. (2017). Remote sensing for restoration planning: How the big picture can inform stakeholders: Remote sensing for restoration planning. *Restoration Ecology*, *25*, S147–S154. doi:10.1111/rec.12448

Cordell, S., & Sandquist, D. R. (2008). The impact of an invasive African bunchgrass (*Pennisetum setaceum*) on water availability and productivity of canopy trees within a tropical dry forest in Hawaii. *Functional Ecology*, *22*(6), 1008–1017. doi:10.1111/j.1365-2435.2008.01471.x

Craven, D., Knight, T., Barton, K., Bialic-Murphy, L., Cordell, S., Giardina, C., Gillespie, T., Ostertag, R., Sack, L., & Chase, J. (2018). OpenNahele: The open Hawaiian forest plot database. *Biodiversity Data Journal*, *6*, e28406. doi:10.3897/BDJ.6.e28406

de Almeida, D. R. A., Stark, S. C., Valbuena, R., Broadbent, E. N., Silva, T. S. F., de Resende, A. F., Ferreira, M. P., Cardil, A., Silva, C. A., Amazonas, N., Zambrano, A. M. A., & Brancalion, P. H. S. (2020). A new era in forest restoration monitoring. *Restoration Ecology*, *28*(1), 8–11. doi:10.1111/rec.13067

DeVries, B., Verbesselt, J., Kooistra, L., & Herold, M. (2015). Robust monitoring of small-scale forest disturbances in a tropical montane forest using Landsat time series. *Remote Sensing of Environment*, *161*, 107–121. doi:10.1016/j.rse.2015.02.012

Dey, D. C., & Schweitzer, C. J. (2014). Restoration for the Future: Endpoints, Targets, and Indicators of Progress and Success. *Journal of Sustainable Forestry*, *33*(sup1), S43–S65. doi:10.1080/10549811.2014.883999

Dimson, M., & Gillespie, T. W. (2020). Trends in active restoration of tropical dry forest: Methods, metrics, and outcomes. *Forest Ecology and Management*, *467*, 118150. doi:10.1016/j.foreco.2020.118150

Drayton, B., & Primack, R. B. (2012). Success Rates for Reintroductions of Eight Perennial Plant Species after 15 Years. *Restoration Ecology, 20*(3), 299–303. doi:10.1111/j.1526-100X.2011.00860.x

Ellsworth, L. M., Litton, C. M., Dale, A. P., & Miura, T. (2014). Invasive grasses change landscape structure and fire behaviour in Hawaii. *Applied Vegetation Science*, *17*(4), 680–689. doi:10.1111/avsc.12110

Ellsworth, L. M., Litton, C. M., & Leary, J. J. K. (2015). Restoration impacts on fuels and fire potential in a dryland tropical ecosystem dominated by the invasive grass *Megathyrsus maximus*. *Restoration Ecology*, *23*(6), 955–963. doi:10.1111/rec.12263

Falk, D. A., Millar, C. I., & Olwell, M. (Eds.). (1996). *Restoring diversity: Strategies for reintroduction of endangered plants*. Island Press.

Faucette, D. T., Brand, B. G., & Castillo, M. (2008). Restoration of a Dry Forest on the Big Island of Hawaii: The Waikoloa Dry Forest Recovery Project. *Tropical Forestry Change in a Changing World*, *5*, 63–71.

Fensholt, R., & Proud, S. R. (2012). Evaluation of Earth Observation based global long term vegetation trends—Comparing GIMMS and MODIS global NDVI time series. *Remote Sensing of Environment*, *119*, 131–147. doi:10.1016/j.rse.2011.12.015

Forkel, M., Carvalhais, N., Verbesselt, J., Mahecha, M., Neigh, C., & Reichstein, M. (2013). Trend Change Detection in NDVI Time Series: Effects of Inter-Annual Variability and Methodology. *Remote Sensing*, *5*(5), 2113–2144. doi:10.3390/rs5052113

Frazier, A. G., & Giambelluca, T. W. (2017). Spatial trend analysis of Hawaiian rainfall from 1920 to 2012. *International Journal of Climatology*, *37*(5), 2522–2531. doi:10.1002/joc.4862

Friday, J. B., Cordell, S., Giardina, C. P., Inman-Narahari, F., Koch, N., Leary, J. J. K., Litton, C. M., & Trauernicht, C. (2015). Future directions for forest restoration in Hawaiʻi. *New Forests*, *46*(5–6), 733–746. doi:10.1007/s11056-015-9507-3

Gamon, J. A., Field, C. B., Goulden, M. L., Griffin, K. L., Hartley, A. E., Joel, G., Penuelas, J., & Valentini, R. (1995). Relationships Between NDVI, Canopy Structure, and Photosynthesis in Three Californian Vegetation Types. *Ecological Applications*, *5*(1), 28–41. doi:10.2307/1942049

Giambelluca, T. W., Chen, Q., Frazier, A. G., Price, J. P., Chen, Y.-L., Chu, P.-S., Eischeid, J. K., & Delparte, D. M. (2013). Online Rainfall Atlas of Hawaiʻi. *Bulletin of the American Meteorological Society*, *94*(3), 313–316. doi:10.1175/BAMS-D-11-00228.1

Giambelluca, T. W., Shuai, X., Barnes, M. L., Alliss, R. J., Longman, R. J., Miura, T., Chen, Q., Frazier, A. G., Mudd, R. G., Cuo, L., & Businger, A. D. (2014). *Evapotranspiration of Hawaiʻi. Final report submitted to the U.S. Army Corps of Engineers—Honolulu District, and the Commission on Water Resource Management, State of Hawaiʻi.*

Gillespie, T. W., Keppel, G., Pau, S., Price, J. P., Jaffré, T., Meyer, J.-Y., & O'Neill, K. (2011). Floristic Composition and Natural History Characteristics of Dry Forests in the Pacific. *Pacific Science*, *65*(2), 127–141. doi:10.2984/65.2.127

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. doi:10.1016/j.rse.2017.06.031

Griscom, H. P., & Ashton, M. S. (2011). Restoration of dry tropical forests in Central America: A review of pattern and process. *Forest Ecology and Management*, *261*(10), 1564–1579. doi:10.1016/j.foreco.2010.08.027

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, *342*(6160), 850–853. doi:10.1126/science.1244693

Hausner, M. B., Huntington, J. L., Nash, C., Morton, C., McEvoy, D. J., Pilliod, D. S., Hegewisch, K. C., Daudert, B., Abatzoglou, J. T., & Grant, G. (2018). Assessing the effectiveness of riparian restoration projects using Landsat and precipitation data from the cloud-computing application ClimateEngine.org. *Ecological Engineering*, *120*, 432–440. doi:10.1016/j.ecoleng.2018.06.024

Herrick, J. E., Schuman, G. E., & Rango, A. (2006). Monitoring ecological processes for restoration projects. *Journal for Nature Conservation*, *14*(3–4), 161–171. doi:10.1016/j.jnc.2006.05.001

Hilker, T., Lyapustin, A. I., Tucker, C. J., Hall, F. G., Myneni, R. B., Wang, Y., Bi, J., Mendes de Moura, Y., & Sellers, P. J. (2014). Vegetation dynamics and rainfall sensitivity of the Amazon. *Proceedings of the National Academy of Sciences*, *111*(45), 16041–16046. doi:10.1073/pnas.1404870111

Hirsch, R. M., Slack, J. R., & Smith, R. A. (1982). Techniques of trend analysis for monthly water quality data. *Water Resources Research*, *18*(1), 107–121. doi:10.1029/WR018i001p00107

Hoekstra, J. M., Boucher, T. M., Ricketts, T. H., & Roberts, C. (2004). Confronting a biome crisis: Global disparities of habitat loss and protection. *Ecology Letters*, *8*(1), 23–29. doi:10.1111/j.1461-0248.2004.00686.x

Holl, K. D. (2017). Restoring tropical forests from the bottom up. *Science*, *355*(6324), 455–456. doi:10.1126/science.aam5432

Jacobi, J. D., Price, J. P., Fortini, L. B., M, G. I., Samuel, & Berkowitz, P. (2017). *Hawaii Land Cover and Habitat Status* [Data set]. U.S. Geological Survey. doi:10.5066/F7DB80B9

Kendall, M. G. (1975). *Rank Correlation Methods* (4th ed.). Charles Griffin.

Kim, J. Y., Rastogi, G., Do, Y., Kim, D.-K., Muduli, P. R., Samal, R. N., Pattnaik, A. K., & Joo, G.-J. (2015). Trends in a satellite-derived vegetation index and environmental variables in a restored brackish lagoon. *Global Ecology and Conservation*, *4*, 614–624. doi:10.1016/j.gecco.2015.10.010

Madson, A., Dimson, M., Fortini, L. B., Kawelo, K., Ticktin, T., Keir, M., Dong, C., Ma, Z., Beilman, D. W., Kay, K., Ocón, J. P., Gallerani, E., Pau, S., & Gillespie, T. W. (2022). A near four-decade time series shows the Hawaiian Islands have been browning since the 1980s. *Environmental Management*.

Mann, H. B. (1945). Nonparametric Tests Against Trend. *Econometrica*, *13*(3), 245. doi:10.2307/1907187

Matthews, J. W., Spyreas, G., & Endress, A. G. (2009). Trajectories of vegetation-based indicators used to assess wetland restoration progress. *Ecological Applications*, *19*(8), 2093–2107. doi:10.1890/08-1371.1

McKenzie, M. M., Giambelluca, T. W., & Diaz, H. F. (2019). Temperature trends in Hawai‘i: A century of change, 1917–2016. *International Journal of Climatology*, *39*(10), 3987–4001. doi:10.1002/joc.6053

Medeiros, A. C., Allmen, E. I. von, & Chimera, C. G. (2014). Dry Forest Restoration and Unassisted Native Tree Seedling Recruitment at Auwahi, Maui. *Pacific Science*, *68*(1), 33–45. doi:10.2984/68.1.3

Menges, E. S. (2008). Restoration demography and genetics of plants: When is a translocation successful? *Australian Journal of Botany*, *56*(3), 187. doi:10.1071/BT07173

Munyati, C., & Mboweni, G. (2013). Variation in NDVI values with change in spatial resolution for semi-arid savanna vegetation: A case study in northwestern South Africa. *International Journal of Remote Sensing*, *34*(7), 2253–2267. doi:10.1080/01431161.2012.743692

Murphy, P. G., & Lugo, A. E. (1986). Ecology of tropical dry forest. *Annual Review of Ecology and Systematics*, *17*(1), 67–88. doi:10.1146/annurev.es.17.110186.000435

Oahu Army Natural Resources Program. (2020). *Ecosystem Restoration Management Plan MU: Keaau Hibiscus*.

O‘ahu Army Natural Resources Program. (2021). *Ecosystem Restoration Management Plan MU: Ohikilolo Lower*.

Pau, S., Okin, G. S., & Gillespie, T. W. (2010). Asynchronous Response of Tropical Forest Leaf Phenology to Seasonal and El Niño-Driven Drought. *PLoS ONE*, *5*(6), e11325. doi:10.1371/journal.pone.0011325

Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J.-M., Tucker, C. J., & Stenseth, N. Chr. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology & Evolution*, *20*(9), 503–510. doi:10.1016/j.tree.2005.05.011

Quesada, M., Sanchez-Azofeifa, G. A., Alvarez-Añorve, M., Stoner, K. E., Avila-Cabadilla, L., Calvo-Alvarado, J., Castillo, A., Espírito-Santo, M. M., Fagundes, M., Fernandes, G. W., Gamon, J., Lopezaraiza-Mikel, M., Lawrence, D., Morellato, L. P. C., Powers, J. S., Neves, F. de S., Rosas-Guerrero, V., Sayago, R., & Sanchez-Montoya, G. (2009). Succession and management of tropical dry forests in the Americas: Review and new perspectives. *Forest Ecology and Management*, *258*(6), 1014–1024. doi:10.1016/j.foreco.2009.06.023

Reis, B. P., Martins, S. V., Fernandes Filho, E. I., Sarcinelli, T. S., Gleriani, J. M., Leite, H. G., & Halassy, M. (2019). Forest restoration monitoring through digital processing of high resolution images. *Ecological Engineering*, *127*, 178–186. doi:10.1016/j.ecoleng.2018.11.022

Roy, D. P., Kovalskyy, V., Zhang, H. K., Vermote, E. F., Yan, L., Kumar, S. S., & Egorov, A. (2016). Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. *Remote Sensing of Environment*, *185*, 57–70. doi:10.1016/j.rse.2015.12.024

Sanchez-Azofeifa, G. A., Quesada, M., Rodriguez, J. P., Nassar, J. M., Stoner, K. E., Castillo, A., Garvin, T., Zent, E. L., Calvo-Alvarado, J. C., Kalacska, M. E. R., Fajardo, L., Gamon, J. A., & Cuevas-Reyes, P. (2005). Research Priorities for Neotropical Dry Forests. *Biotropica*, *37*(4), 477–485. doi:10.1111/j.1744-7429.2005.00066.x

Secades, C., O’Connor, B., Brown, C., & Walpole, M. (2014). *Earth Observation for Biodiversity Monitoring: A review of current approaches and future opportunities for tracking progress towards the Aichi Biodiversity Targets* (No. 72; Technical Series, p. 183). Secretariat of the Convention on Biological Diversity.

Somers, B., & Asner, G. P. (2013). Multi-temporal hyperspectral mixture analysis and feature selection for invasive species mapping in rainforests. *Remote Sensing of Environment*, *136*, 14–27. doi:10.1016/j.rse.2013.04.006

Stanturf, J. A., Palik, B. J., & Dumroese, R. K. (2014). Contemporary forest restoration: A review emphasizing function. *Forest Ecology and Management*, *331*, 292–323. doi:10.1016/j.foreco.2014.07.029

Stone, C. P., Smith, C. W., Tunison, J. T., & Cooperative National Park Resources Studies Unit, Hawaii (Eds.). (1992). *Alien plant invasions in native ecosystems of Hawai‘i: Management and research*. University of Hawaii, Cooperative National Park Resources Studies Unit.

Suding, K. N. (2011). Toward an Era of Restoration in Ecology: Successes, Failures, and Opportunities Ahead. *Annual Review of Ecology, Evolution, and Systematics*, *42*(1), 465–487. doi:10.1146/annurev-ecolsys-102710-145115

Sun, Z., Chang, N.-B., Opp, C., & Hennig, T. (2011). Evaluation of ecological restoration through vegetation patterns in the lower Tarim River, China with MODIS NDVI data. *Ecological Informatics*, *6*(2), 156–163. doi:10.1016/j.ecoinf.2010.10.002

Sunderland, T., Apgaua, D., Baldauf, C., Blackie, R., Colfer, C., Cunningham, A. B., Dexter, K., Djoudi, H., Gautier, D., Gumbo, D., Ickowitz, A., Kassa, H., Parthasarathy, N., Pennington,

R. T., Paumgarten, F., Pulla, S., Sola, P., Tng, D., Waeber, P., & Wilmé, L. (2015). Global dry forests: A prologue. *International Forestry Review*, *17*(2), 1–9. doi:10.1505/146554815815834813

Trauernicht, C. (2019). Vegetation—Rainfall interactions reveal how climate variability and climate change alter spatial patterns of wildland fire probability on Big Island, Hawaii. *Science of The Total Environment*, *650*, 459–469. doi:10.1016/j.scitotenv.2018.08.347

Tuxen, K. A., Schile, L. M., Kelly, M., & Siegel, S. W. (2008). Vegetation Colonization in a Restoring Tidal Marsh: A Remote Sensing Approach. *Restoration Ecology*, *16*(2), 313–323. doi:10.1111/j.1526-100X.2007.00313.x

Verbesselt, J., Hyndman, R., Newnham, G., & Culvenor, D. (2010). Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment*, *114*(1), 106–115. doi:10.1016/j.rse.2009.08.014

Verbesselt, J., Hyndman, R., Zeileis, A., & Culvenor, D. (2010). Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. *Remote Sensing of Environment*, *114*(12), 2970–2980. doi:10.1016/j.rse.2010.08.003

Xu, Z., Cao, L., Zhong, S., Liu, G., Yang, Y., Zhu, S., Luo, X., & Di, L. (2020). Trends in Global Vegetative Drought From Long-Term Satellite Remote Sensing Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 815–826. doi:10.1109/JSTARS.2020.2972574

Xue, J., & Su, B. (2017). Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of Sensors*, *2017*, 1–17. doi:10.1155/2017/1353691

Zhang, G., Dong, J., Xiao, X., Hu, Z., & Sheldon, S. (2012). Effectiveness of ecological restoration projects in Horqin Sandy Land, China based on SPOT-VGT NDVI data. *Ecological Engineering*, *38*(1), 20–29. doi:10.1016/j.ecoleng.2011.09.005

Zhou, L., Tian, Y., Myneni, R. B., Ciais, P., Saatchi, S., Liu, Y. Y., Piao, S., Chen, H., Vermote, E. F., Song, C., & Hwang, T. (2014). Widespread decline of Congo rainforest greenness in the past decade. *Nature*, *509*(7498), 86–90. doi:10.1038/nature13265

Zhu, Z., Piao, S., Myneni, R. B., Huang, M., Zeng, Z., Canadell, J. G., Ciais, P., Sitch, S., Friedlingstein, P., Arneth, A., Cao, C., Cheng, L., Kato, E., Koven, C., Li, Y., Lian, X., Liu, Y., Liu, R., Mao, J., … Zeng, N. (2016). Greening of the Earth and its drivers. *Nature Climate Change*, *6*(8), 791–795. doi:10.1038/nclimate3004

Chapter 5. Conclusions

Continuous, large-scale monitoring is necessary to evaluate biodiversity conservation policy and to inform adaptive management strategies. However, monitoring is generally deficient, particularly for plant taxa, invasive species, and in areas with high rates of endemism (Hochkirch et al., 2021). Alternatives to conventional, standardized surveys, which are valuable but limited in spatial and temporal extent, must be considered (Kühl et al., 2020). This dissertation examined biodiversity monitoring applications for publicly accessible geospatial datasets, including iNaturalist citizen science observations and Landsat imagery, in the Hawaiian Islands, a biodiversity hotspot.

Understanding the citizen science observation process can help data users to account for biases generated by low-structure sampling schemes (Kelling et al., 2019). Chapter 2 of the dissertation asked how participation in the citizen science app iNaturalist has changed over time. iNaturalist activity has been spatially biased toward developed and more accessible sites, particularly among the least active observers. Participation grew exponentially until early 2020, then decreased immediately after COVID-19 travel restrictions began. This was most likely due to a decline in visitors, who were more active and numerous than residents, made the majority of species observations, and were more likely to make research-grade observations. Resident activity was relatively more stable, and existing spatial biases in the data increased slightly.

COVID-19 lockdowns in other regions were associated with similar effects, including spatial restrictions to more accessible sites and greater reliance on more active citizen science participants (Crimmins et al., 2021; Kishimoto & Kobori, 2021; Sánchez-Clavijo et al., 2021). This study corroborates those findings, but also highlights the role of travel in citizen science data collection in Hawaii. The majority of Hawaii's iNaturalist observers, and the most active ones, are unlikely to live in Hawaii. When tourism was restricted, fewer species observations were made. Thus, local participation is needed to support stable, continuous biodiversity monitoring via citizen science, particularly under extraordinary social circumstances. Furthermore, differing sampling patterns between more and less active observers suggest that encouraging more sustained participation could improve the spatial and taxonomic diversity of observations. Additional work is needed to explore why observer characteristics (visitor vs. resident, more vs. less active) are associated with different spatial sampling patterns in particular, and whether those patterns are driven by unequal access or actual preference.

Chapter 3 focused on iNaturalist plant observations, and asked whether citizen science could increase the extent of professional invasive plant monitoring and be used to improve estimates of habitat. Though iNaturalist spatial bias toward more accessible, disturbed sites was greater in non-native species observations, non-native plants—and invasive species especially—were disproportionately well-sampled compared to endemic and indigenous species. Analysis of four example invasive species showed that professional agency observations exhibit similar or inverse spatial bias patterns. Habitat suitability models for the four invasive species often produced distinct predictions with iNaturalist vs. agency data, particularly in disturbed vs. native vegetation-dominated sites. Stratifying or filtering the iNaturalist observations before modeling, however, had little effect on predictions of habitat suitability.

Though preferences for threatened or rarer species have been observed in citizen science data for other taxonomic groups (Matteson et al., 2012; Tulloch et al., 2013), my results suggest that iNaturalist is a promising source of non-native and invasive plant monitoring data in Hawaii. While data stratification was limited in its capacity to improve habitat suitability models based on iNaturalist observations alone, the spatial biases in iNaturalist and professional agency data can be complementary, and combining data from both sources led to more comprehensive estimates of suitable habitat. Citizen science could thus be used to fill monitoring gaps in areas excluded from official surveys. In Hawaii, this often means more disturbed areas. But agencies in other regions could use known biases to guide their own survey resources and utilize citizen science as a complementary data source for modeling and other applications. Future work could observe broader-scale patterns by considering additional species or regions, or explore the effects of more targeted data integration methods (Fletcher et al., 2019).

Chapter 4 asked how remotely sensed Normalized Difference Vegetation Index (NDVI) time series could be used to facilitate tropical dry forest and restoration site monitoring. Significant increases in Landsat-derived median NDVI were observed at the majority of native, non-native, and restored dry forest study sites from 1999-2022. Median NDVI trends were more variable at smaller restoration sites where management began more recently, but corresponded with reported outcomes at the more established Makauwahi and Auwahi restoration sites. Additionally, breakpoints in NDVI trends at Makauwahi aligned with major management activities. A positive relationship was detected between median NDVI and the long-term precipitation anomaly at most sites, but was stronger in non-native dry grassland.

The positive NDVI trends in this chapter deviate from coarser spatial resolution studies (e.g. 250-meter and 5-kilometer resolution), which have reported declines in NDVI driven by long-term drying in Hawaii (Barbosa & Asner, 2016; Madson et al., 2022). It is likely that 30-meter resolution Landsat imagery is more appropriate for monitoring Hawaii’s highly fragmented dry forest patches. At this scale, dry forest trends appear to be discernible from those of adjacent vegetation types, such as non-native grassland, that are more closely linked to anomalous precipitation conditions. Further study of drought and other potential climate factors is needed to better understand the drivers behind these site-level NDVI trends. However, these results highlight the value of Hawaii’s remaining dry forests, which appear to be increasing in productivity despite downward rainfall trends, as well as the importance of dry forest restoration. Time series of NDVI parameters and other remotely sensed metrics at Landsat or finer resolution have great potential to aid and extend monitoring efforts in this rare and threatened ecosystem.

This research investigated biodiversity monitoring applications for geospatial datasets in the Hawaiian Islands. Though these datasets do not serve as direct substitutes for standardized, in situ biodiversity monitoring, they are readily accessible, offer near global coverage, and could support monitoring schemes in other regions where resources for conventional surveys are limited. The results of this dissertation demonstrate that utilizing multiple data sources can enhance the breadth and continuity of biodiversity monitoring in understudied areas and during periods of sociopolitical uncertainty.

References

Barbosa, J. M., & Asner, G. P. (2016). Effects of long-term rainfall decline on the structure and functioning of Hawaiian forests. *Environmental Research Letters, 12*(9), 094002. doi:10.1088/1748-9326/aa7ee4

Crimmins, T. M., Posthumus, E., Schaffer, S., & Prudic, K. L. (2021). COVID-19 impacts on participation in large scale biodiversity-themed community science projects in the United States. *Biological Conservation, 256*, 109017. doi:10.1016/j.biocon.2021.109017

Fletcher, R. J., Hefley, T. J., Robertson, E. P., Zuckerberg, B., McCleery, R. A., & Dorazio, R. M. (2019). A practical guide for combining data to model species distributions. *Ecology*, e02710. doi:10.1002/ecy.2710

Hochkirch, A., Samways, M. J., Gerlach, J., Böhm, M., Williams, P., Cardoso, P., Cumberlidge, N., Stephenson, P. J., Seddon, M. B., Clausnitzer, V., Borges, P. A. V., Mueller, G. M., Pearce-Kelly, P., Raimondo, D. C., Danielczak, A., & Dijkstra, K. B. (2021). A strategy for the next decade to address data deficiency in neglected biodiversity. *Conservation Biology, 35*(2), 502–509. doi:10.1111/cobi.13589

Kelling, S., Johnston, A., Bonn, A., Fink, D., Ruiz-Gutierrez, V., Bonney, R., Fernandez, M., Hochachka, W. M., Julliard, R., Kraemer, R., & Guralnick, R. (2019). Using Semistructured Surveys to Improve Citizen Science Data for Monitoring Biodiversity. *BioScience*, *69*(3), 170–179. doi:10.1093/biosci/biz010

Kishimoto, K., & Kobori, H. (2021). COVID-19 pandemic drives changes in participation in citizen science project “City Nature Challenge” in Tokyo. *Biological Conservation*, *255*, 109001. doi:10.1016/j.biocon.2021.109001

Kühl, H. S., Bowler, D. E., Bösch, L., Bruelheide, H., Dauber, J., Eichenberg, David., Eisenhauer, N., Fernández, N., Guerra, C. A., Henle, K., Herbinger, I., Isaac, N. J. B., Jansen, F., König-Ries, B., Kühn, I., Nilsen, E. B., Pe’er, G., Richter, A., Schulte, R., … Bonn, A. (2020). Effective Biodiversity Monitoring Needs a Culture of Integration. *One Earth*, *3*(4), 462–474. doi:10.1016/j.oneear.2020.09.010

Madson, A., Dimson, M., Fortini, L. B., Kawelo, K., Ticktin, T., Keir, M., Dong, C., Ma, Z., Beilman, D. W., Kay, K., Ocón, J. P., Gallerani, E., Pau, S., & Gillespie, T. W. (2022). A near four-decade time series shows the Hawaiian Islands have been browning since the 1980s. *Environmental Management*.

Matteson, K. C., Taron, D. J., & Minor, E. S. (2012). Assessing Citizen Contributions to Butterfly Monitoring in Two Large Cities. *Conservation Biology*, *26*(3), 557–564. doi:10.1111/j.1523-1739.2012.01825.x

Sánchez-Clavijo, L. M., Martínez-Callejas, S. J., Acevedo-Charry, O., Diaz-Pulido, A., Gómez-Valencia, B., Ocampo-Peñuela, N., Ocampo, D., Olaya-Rodríguez, M. H., Rey-Velasco, J. C., Soto-Vargas, C., & Ochoa-Quintero, J. M. (2021). Differential reporting of biodiversity in two citizen science platforms during COVID-19 lockdown in Colombia. *Biological Conservation*, *256*, 109077. doi:10.1016/j.biocon.2021.109077

Tulloch, A. I. T., Mustin, K., Possingham, H. P., Szabo, J. K., & Wilson, K. A. (2013). To boldly go where no volunteer has gone before: Predicting volunteer activity to prioritize surveys at the landscape scale. *Diversity and Distributions*, *19*(4), 465–480. doi:10.1111/j.1472-4642.2012.00947.x

Appendix A

Supplementary Material for Chapter 2. Who, where, when: Observer behavior influences spatial and temporal patterns of iNaturalist participation.

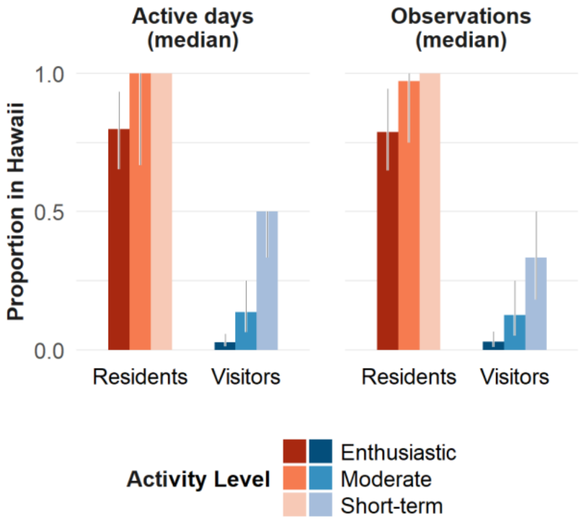


Figure A1
Median proportion of activity (observations and active days) in Hawaii for residents versus visitors (lines show interquartile range).

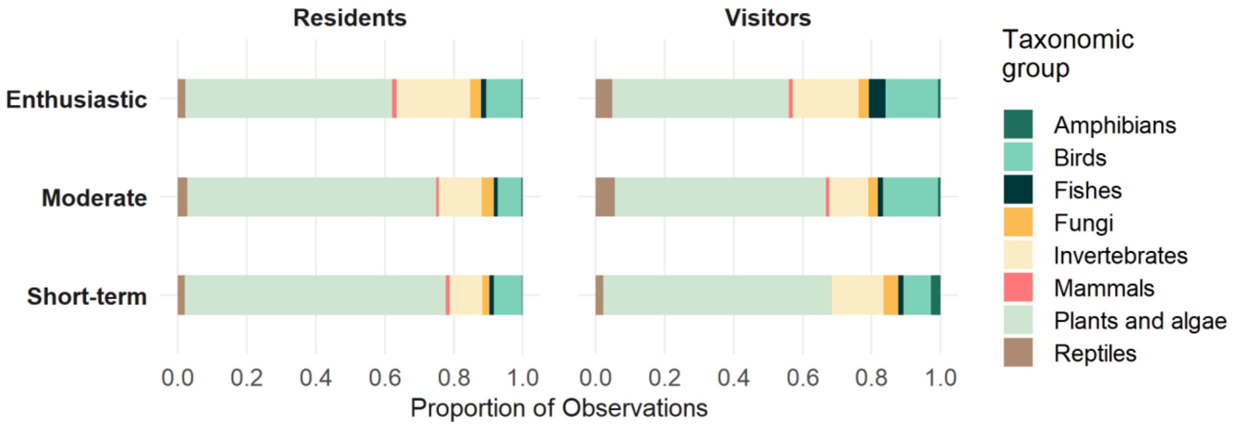


Figure A2

Observations of each taxonomic group by observer behavior (classified by location x activity).

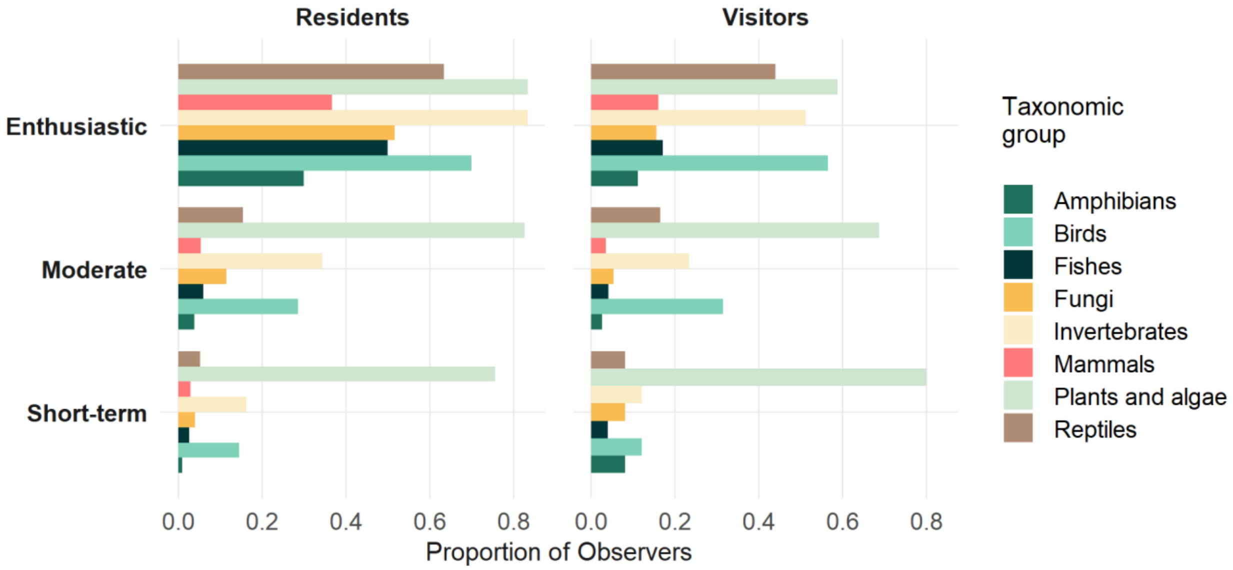


Figure A3

Proportion of observers (classified by location x activity) who made at least one observation of a given taxonomic group.

Table A1

Slope of regression, adjusted r^2, and statistical significance (sig; * $p \leq 0.05$, ** $p \leq 0.01$, *** $p < 0.001$) for log-transformed observations, unique observers, and new observers versus year for 2008-2019.

	ln(observations)			ln(unique observers)			ln(new observers)		
	slope	r^2	sig	slope	r^2	sig	slope	r^2	sig
All data	0.56	0.92	***	0.52	0.94	***	0.52	0.93	***
Observer behavior									
Resident - enthusiastic	0.85	0.93	***	0.39	0.88	***	0.18	0.55	*
Resident - moderate	0.88	0.86	***	0.78	0.97	***	0.76	0.97	***
Resident - short-term	1.00	0.68	*	0.86	0.84	**	0.86	0.84	**
Visiting - enthusiastic	0.45	0.88	***	0.34	0.95	***	0.31	0.95	***
Visiting - moderate	0.94	0.88	***	0.8	0.87	***	0.8	0.87	***
Visiting short-term	-0.39	0.02	*none*	-0.26	-0.12	*none*	-0.26	-0.12	*none*
Observation quality									
Research-grade	0.51	0.90	***	0.5	0.95	***			
Needs ID	0.69	0.90	***	0.62	0.96	***			
Casual	0.72	0.90	***	0.63	0.91	***			
Taxonomic group									
Amphibians	0.39	0.75	***	0.42	0.83	***			
Birds	0.49	0.93	***	0.5	0.93	***			
Fishes	0.40	0.85	***	0.43	0.9	***			
Fungi	0.59	0.78	***	0.53	0.87	***			
Invertebrates	0.59	0.85	***	0.53	0.93	***			
Mammals	0.51	0.87	***	0.47	0.87	***			
Plants & algae	0.63	0.92	***	0.59	0.93	***			
Reptiles	0.44	0.84	***	0.46	0.93	***			
Land cover									
Developed	0.62	0.95	***	0.56	0.94	***			
Agriculture	0.56	0.86	***	0.49	0.91	***			
Bare Ground	0.45	0.86	***	0.46	0.91	***			
Grassland	0.60	0.87	***	0.53	0.9	***			
Dry/Mesic Shrubland	0.55	0.81	***	0.48	0.89	***			
Dry/Mesic Forest	0.59	0.84	***	0.52	0.94	***			
Wet Forest/Shrubland	0.52	0.88	***	0.49	0.92	***			
Wetland	0.63	0.75	**	0.64	0.98	***			
Distance to road/trail									
≤ 150 m	0.57	0.90	***	0.52	0.93	***			
≤ 553.2 m	0.59	0.90	***	0.55	0.95	***			
≤ 1513.4 m	0.48	0.78	***	0.48	0.91	***			
> 1513.4 m	0.42	0.81	***	0.46	0.94	***			
Land designation									
None	0.55	0.88	***	0.53	0.94	***			
Limited protection	0.61	0.90	***	0.56	0.95	***			
Multi-use	0.58	0.92	***	0.5	0.91	***			
For biodiversity	0.52	0.8	***	0.43	0.82	***			

Table A2

Pair-wise comparison of observer behavior trends in log-transformed observations, unique observers, and new observers versus year for 2008-2019. Asterisks indicate significant difference (* p ≤ 0.05, ** p ≤ 0.01, *** p <0.001).

Observations

	Resident - Enthusiastic	Resident - Moderate	Resident - Short-term	Visiting- Enthusiastic	Visiting- Moderate
Resident-Moderate	-0.033	-			
Resident-Short-term	-0.151	-0.118	-		
Visiting-Enthusiastic	* 0.397	0.430	* 0.548	-	
Visiting-Moderate	-0.093	-0.060	0.058	* -0.490	-
Visiting-Short-term	1.236	1.269	* 1.387	0.839	* 1.329

Unique Observers

	Resident - Enthusiastic	Resident - Moderate	Resident - Short-term	Visiting- Enthusiastic	Visiting- Moderate
Resident-Moderate	* -0.388	-			
Resident-Short-term	* -0.471	-0.083	-		
Visiting-Enthusiastic	0.052	*** 0.440	*** 0.523	-	
Visiting-Moderate	* -0.414	-0.026	0.057	*** -0.465	-
Visiting-Short-term	0.651	** 1.039	** 1.122	0.599	** 1.065

New Observers

	Resident - Enthusiastic	Resident - Moderate	Resident - Short-term	Visiting- Enthusiastic	Visiting- Moderate
Resident-Moderate	*** -0.572	-			
Resident-Short-term	*** -0.675	-0.103	-		
Visiting-Enthusiastic	-0.131	*** 0.441	*** 0.544	-	
Visiting-Moderate	*** -0.613	-0.041	0.062	*** -0.482	-
Visiting-Short-term	0.447	* 1.019	** 1.122	0.578	** 1.060

Table A3

Difference, by quarter, between observed and predicted observations in 2020-2021, based on linear models of log-transformed observations from 2008-2019. Significant differences (*) determined by 95% confidence interval.

	2020				2021			
	JFM	AMJ	JAS	OND	JFM	AMJ	JAS	OND
All observations	20.5	-57.7	-65.8	-74.8	-22.5	-7.1	-17.9	-57.5
Observer behavior								
Resident - Enthusiastic	-75.1	-40.5	-40.7	-77.0	-71.0	-12.4	-22.5	-74.4
Resident - Moderate	-63.0	-61.8	-42.7	-25.1	-62.3	-74.8	-67.2	-32.1
Resident - Short-term	-75.1	34.7	-85.3	-80.4	-58.7	406.8	-82.4	-92.2
Visiting - Enthusiastic	113.1	*-92.6	*-94.7	-84.0	-9.6	54.0	-32.8	-46.4
Visiting - Moderate	-68.4	-93.4	*-93.2	-56.1	-92.8	-77.5	-73.6	-24.2
Observation quality								
Casual	2.5	-57.2	-66.0	-78.8	-48.6	-40.6	-45.6	-70.4
Needs ID	-32.4	-58.8	-72.5	-74.5	-44.7	-7.5	-44.6	-56.3
Research-grade	51.8	-53.9	-66.9	-71.2	-11.5	16.6	-2.4	-49.0
Taxonomic group								
Amphibians	447.0	-68.3	-80.5	-40.3	55.1	55.2	-49.8	16.1
Birds	51.6	-80.3	-79.2	-77.7	-35.4	-42.0	0.6	-44.4
Fishes	241.0	-52.0	-77.4	-0.7	37.1	69.4	-11.8	129.0
Fungi	44.5	-37.5	-42.6	-36.8	32.7	-15.3	-31.4	-44.9
Invertebrates	22.9	-47.5	-73.6	-70.6	-29.1	6.0	-49.0	-46.2
Mammals	22.6	-59.1	-50.0	*-87.3	-37.2	-9.3	65.7	-63.5
Plants and algae	1.9	-51.7	-72.2	-74.4	-28.1	1.3	-42.7	-59.8
Reptiles	96.2	*-70.4	-54.7	-72.3	-23.3	-28.6	29.4	-52.9
Land cover								
Developed	9.5	-62.8	-56.3	-80.4	-34.7	-47.3	-22.1	-69.7
Agriculture	-2.4	-47.6	-24.5	-52.6	-43.7	-22.9	49.7	-39.7
Bare Ground	86.9	-68.9	*-86.9	-58.9	-9.0	66.0	-38.1	11.8
Grassland	40.2	-53.9	-60.2	-55.7	-0.1	18.4	-6.9	-51.8
Dry/Mesic Shrubland	36.6	-79.7	-73.3	-79.1	6.1	-16.8	86.2	-65.8
Dry/Mesic Forest	61.0	-65.5	-80.8	-59.5	7.0	1.4	-56.0	-14.7
Wet Forest/Shrubland	-19.0	-33.7	-72.9	-27.1	-6.8	166.9	15.0	50.8
Wetland	-21.9	-40.8	*-89.4	-70.7	*-77.5	290.3	-31.7	-67.7
Distance to road/trail								
≤ 150 m	12.5	-53.6	-64.3	-74.4	-29.5	-2.6	-19.3	-60.1
≤ 553.2 m	94.0	-79.6	*-82.7	-48.9	16.5	-46.9	-46.5	5.4
≤ 1513.4 m	68.3	-31.0	-71.3	-51.4	136.6	79.5	-32.4	190.6
> 1513.4 m	19.6	-49.8	-52.2	-23.1	7.3	91.2	-5.8	57.4
Land designation								
None	68.3	-31.2	-59.7	-69.6	10.9	18.8	-15.2	-53.4
Limited protection	-31.9	-62.2	-63.2	-63.5	-59.5	-14.3	-9.0	-23.8
Multi-use	-5.8	-59.3	-61.6	-53.5	-12.0	66.6	8.8	-15.2
For biodiversity	94.3	-90.2	-88.8	-72.7	-50.8	8.5	-33.3	-18.0

Table A4

Difference, by quarter, between the number of observed and predicted unique observers in 2020-2021, based on linear models of log-transformed unique observers from 2008-2019. Significant differences (*) determined by 95% confidence interval.

	2020				2021			
	JFM	AMJ	JAS	OND	JFM	AMJ	JAS	OND
All unique observers	34.0	-60.3	-44.4	-56.5	-24.9	-25.9	9.5	-42.5
Observer behavior								
Resident - Enthusiastic	-0.9	-12.7	-39.1	-52.1	-35.4	-16.6	-44.6	*-66.5
Resident - Moderate	-31.3	-26.5	-39.1	-47.4	-48.6	-49.9	-66.2	-71.3
Resident - Short-term	-50.7	14.7	-74.1	-81.1	-45.7	141.4	-64.5	-86.2
Visiting - Enthusiastic	39.2	*-90.7	*-88.9	*-83.2	-58.2	-17.3	-6.1	-43.5
Visiting - Moderate	-53.2	*-95.3	*-90.0	-59.6	-89.0	*-80.1	-66.2	-22.4
Observation quality								
Casual	75.2	-61.0	-41.2	-70.8	-1.3	-42.3	8.8	-63.2
Needs ID	33.5	-63.4	-55.4	-62.9	-16.5	-40.1	-31.8	-58.5
Research-grade	22.7	-59.5	-50.5	-60.2	-41.1	-19.6	11.6	-44.7
Taxonomic group								
Amphibians	253.7	-68.1	-78.0	-37.4	22.6	38.1	-61.1	14.2
Birds	46.7	*-75.1	-67.7	-71.5	-34.8	-22.6	36.5	-41.5
Fishes	38.1	-30.0	-41.4	-24.6	6.4	83.5	68.6	56.6
Fungi	178.1	-51.3	-20.9	-27.4	118.6	2.4	21.6	-30.2
Invertebrates	63.3	-48.2	-53.5	-59.2	1.3	-0.8	-17.6	-54.8
Mammals	71.5	-66.3	-48.5	*-86.8	-1.1	-28.6	81.4	-56.6
Plants and algae	79.0	-62.3	-45.6	-42.0	2.5	-38.6	1.4	-24.6
Reptiles	62.0	-53.7	-54.9	-63.7	-22.2	8.1	15.6	-38.9
Land cover								
Developed	34.0	-62.1	-36.9	-61.6	-28.0	-35.6	17.3	-49.7
Agriculture	90.9	-47.0	-37.3	-37.4	-9.4	-4.6	51.2	-32.1
Bare Ground	119.1	-64.2	-71.3	-55.2	14.5	31.6	23.6	14.6
Grassland	96.0	-54.7	-46.2	-57.9	5.8	9.1	36.6	-52.8
Dry/Mesic Shrubland	56.8	-70.1	-42.6	-58.7	-0.9	-26.3	193.2	-34.9
Dry/Mesic Forest	69.1	-65.8	-64.2	-47.6	-20.4	-16.5	-15.0	-22.4
Wet Forest/Shrubland	36.4	-57.7	-56.4	-46.9	-19.3	0.3	9.1	-12.6
Wetland	-20.5	-64.2	-73.3	-60.6	-68.5	61.6	12.0	-32.5
Distance to road/trail								
≤ 150 m	37.4	-57.2	-44.0	-55.0	-22.8	-20.0	11.9	-39.9
≤ 553.2 m	82.1	-71.9	*-79.1	-64.3	-9.2	-38.2	-41.9	-47.1
≤ 1513.4 m	63.0	-42.4	-54.7	-48.0	-13.3	-2.7	-42.4	-15.7
> 1513.4 m	-7.4	-53.0	-44.7	-44.8	-47.4	-9.8	4.5	-5.6
Land designation								
None	58.8	-54.2	-40.0	-57.0	-10.1	-14.5	16.1	-48.1
Limited protection	11.0	-65.4	-52.8	*-74.7	-36.5	-25.4	21.7	-59.3
Multi-use	55.9	-59.6	-58.9	-59.1	-25.6	-11.2	21.6	-34.6
For biodiversity	131.1	-84.7	-64.5	-35.9	-5.0	2.1	43.9	55.8

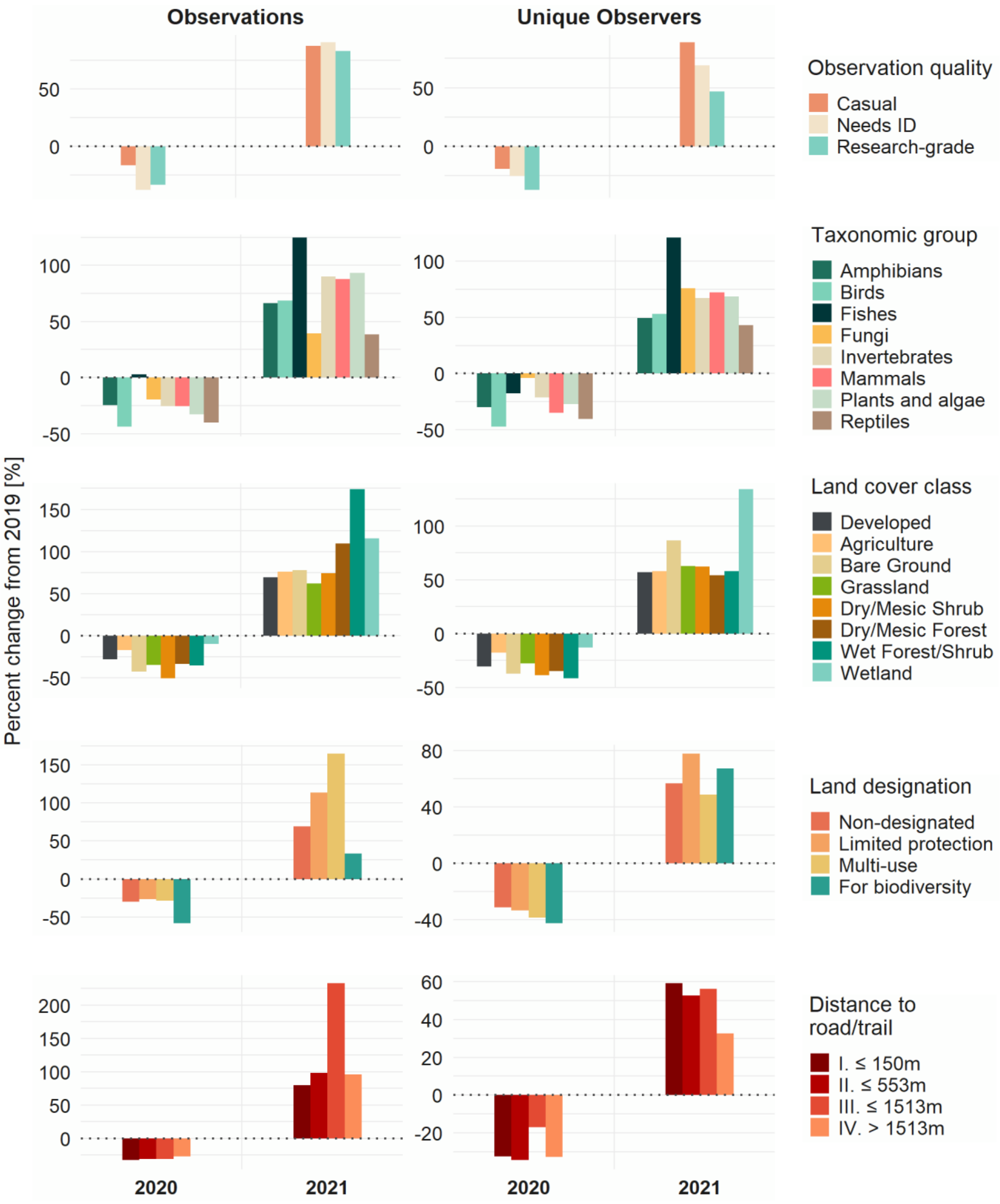


Figure A4

Relative change from 2019 in observations and unique observers by observation quality, taxonomic group, land cover class, land designation, and distance to roads/trails. Unique observers were those who made at least one observation of a given quality.

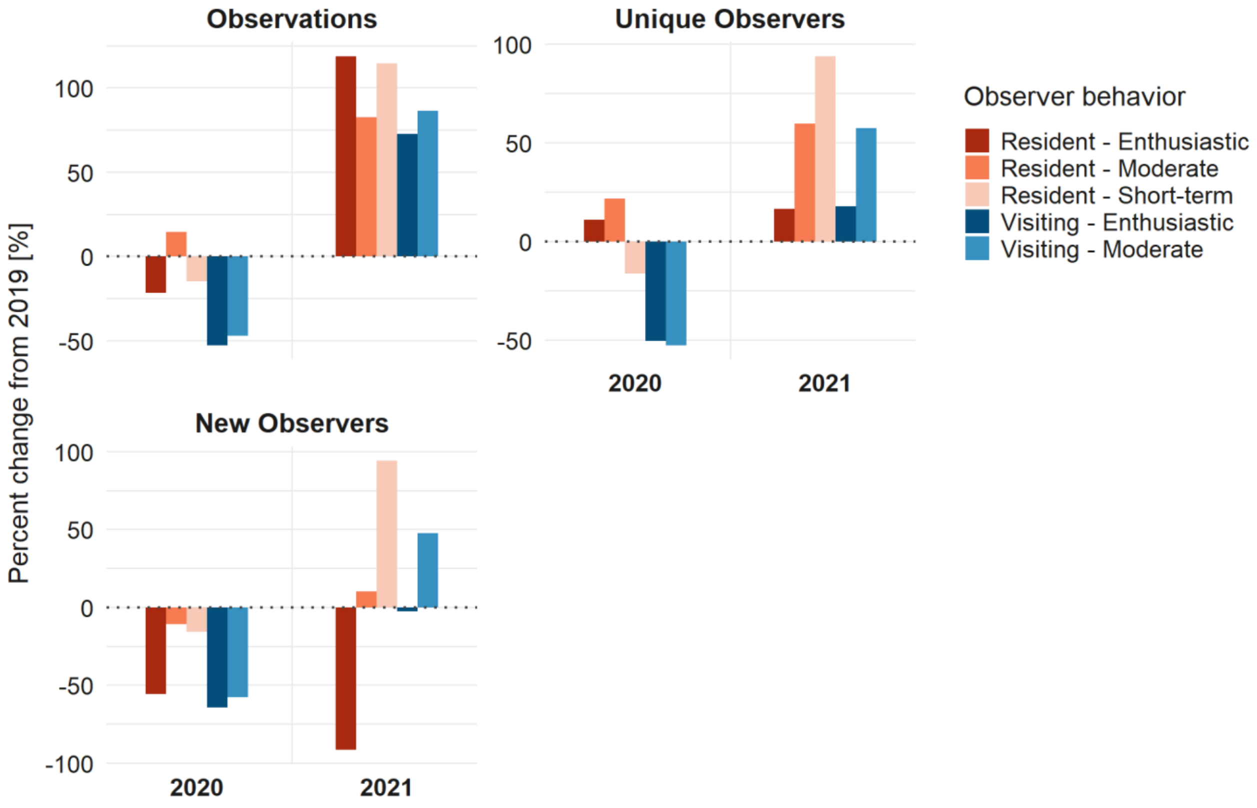


Figure A5

Relative change from 2019 in observations, unique observers, and new observers by observer behavior. Unique observers were those who made at least one observation of a given quality. Visiting-short-term observers were excluded due to low sample size.

Appendix B

Supplementary Material for Chapter 3. Citizen science plant observations complement professional monitoring and improve estimates of invasive species habitat

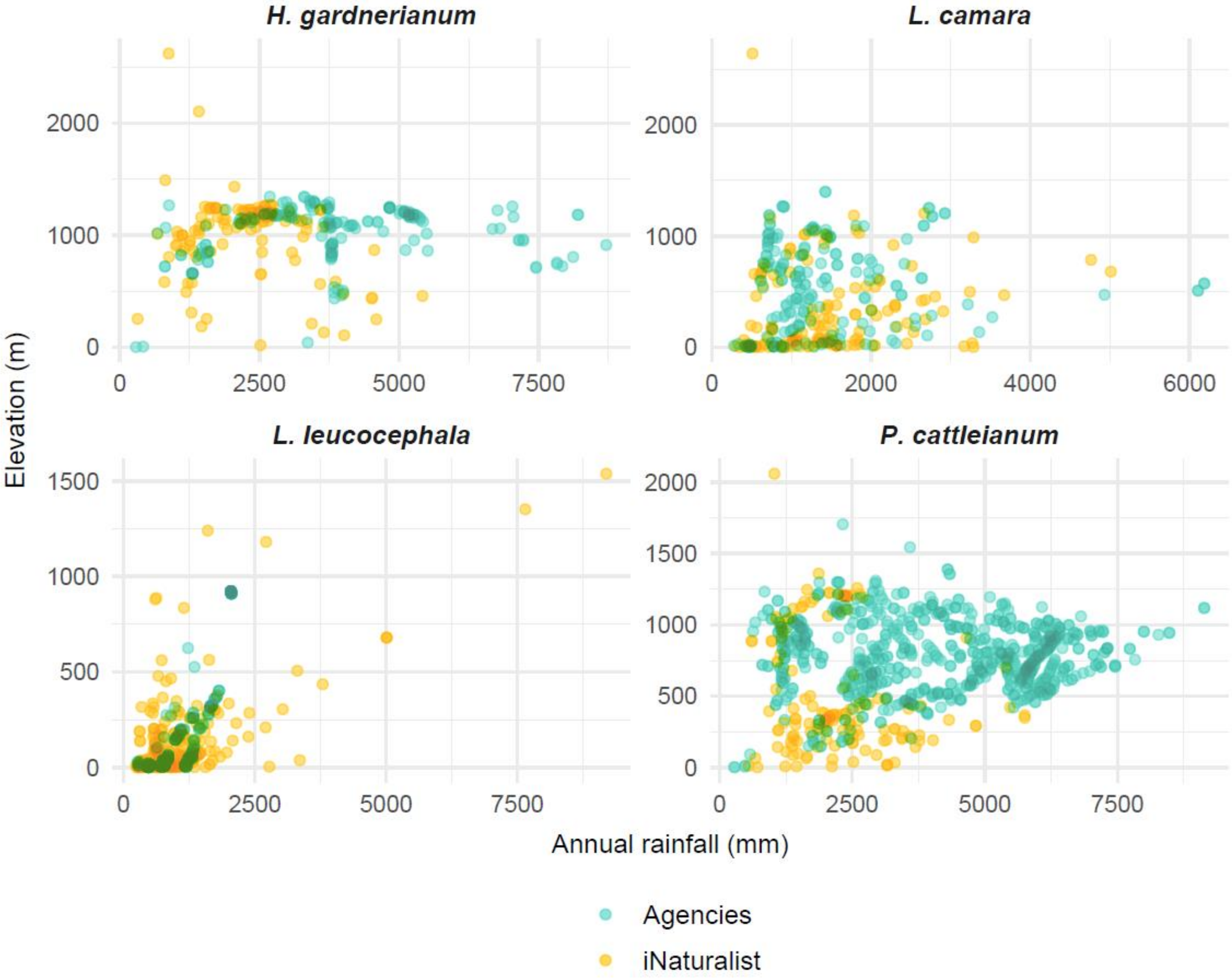


Figure B1
Distribution of iNaturalist and professional management agency observations along elevation and annual rainfall gradients. Despite little overlap in geographic space (Fig. B1), the datasets captured some similar environments.

(a) *Hedychium gardnerianum*

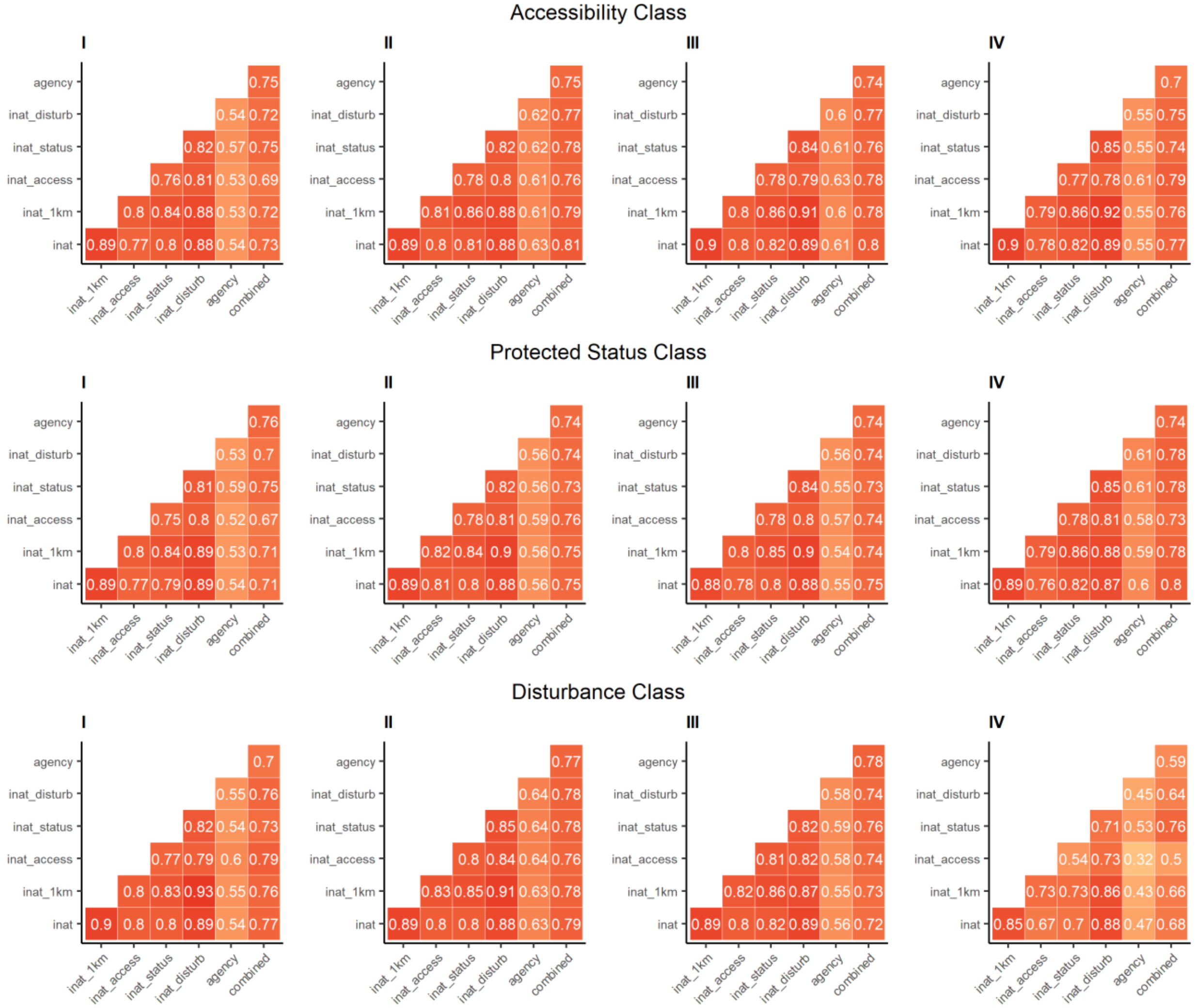
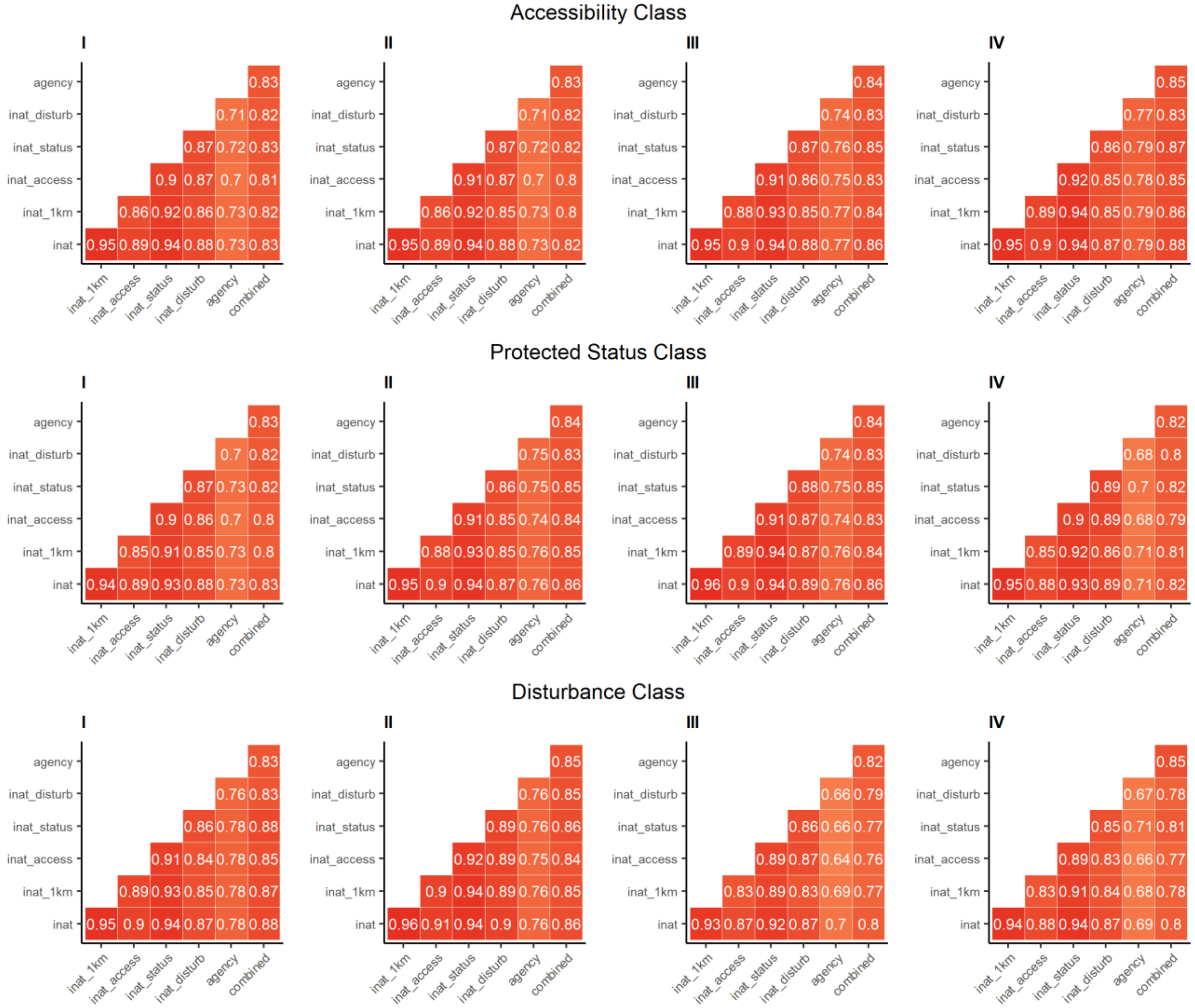


Figure B2

Similarity or overlap (pairwise Schoener's *D* index) between (a) *Hedychium gardnerianum*, (b) *Lantana camara*, (c) *Leucaena leucocephala*, and (d) *Psidium cattleianum* model series within each site class, where 0 signifies no overlap and 1 is complete overlap.

(b) *Lantana camara*



Accessibility Class

I

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.83
inat_disturb					0.71	0.82
inat_status				0.87	0.72	0.83
inat_access			0.9	0.87	0.7	0.81
inat_1km		0.86	0.92	0.86	0.73	0.82
inat	0.95	0.89	0.94	0.88	0.73	0.83

II

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.83
inat_disturb					0.71	0.82
inat_status				0.87	0.72	0.82
inat_access			0.91	0.87	0.7	0.8
inat_1km		0.86	0.92	0.85	0.73	0.8
inat	0.95	0.89	0.94	0.88	0.73	0.82

III

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.84
inat_disturb					0.74	0.83
inat_status				0.87	0.76	0.85
inat_access			0.91	0.86	0.75	0.83
inat_1km		0.88	0.93	0.85	0.77	0.84
inat	0.95	0.9	0.94	0.88	0.77	0.86

IV

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.85
inat_disturb					0.77	0.83
inat_status				0.86	0.79	0.87
inat_access			0.92	0.85	0.78	0.85
inat_1km		0.89	0.94	0.85	0.79	0.86
inat	0.95	0.9	0.94	0.87	0.79	0.88

Protected Status Class

I

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.83
inat_disturb					0.7	0.82
inat_status				0.87	0.73	0.82
inat_access			0.9	0.86	0.7	0.8
inat_1km		0.85	0.91	0.85	0.73	0.8
inat	0.94	0.89	0.93	0.88	0.73	0.83

II

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.84
inat_disturb					0.75	0.83
inat_status				0.86	0.75	0.85
inat_access			0.91	0.85	0.74	0.84
inat_1km		0.88	0.93	0.85	0.76	0.85
inat	0.95	0.9	0.94	0.87	0.76	0.86

III

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.84
inat_disturb					0.74	0.83
inat_status				0.88	0.75	0.85
inat_access			0.91	0.87	0.74	0.83
inat_1km		0.89	0.94	0.87	0.76	0.84
inat	0.96	0.9	0.94	0.89	0.76	0.86

IV

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.82
inat_disturb					0.68	0.8
inat_status				0.89	0.7	0.82
inat_access			0.9	0.89	0.68	0.79
inat_1km		0.85	0.92	0.86	0.71	0.81
inat	0.95	0.88	0.93	0.89	0.71	0.82

Disturbance Class

I

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.83
inat_disturb					0.76	0.83
inat_status				0.86	0.78	0.88
inat_access			0.91	0.84	0.78	0.85
inat_1km		0.89	0.93	0.85	0.78	0.87
inat	0.95	0.9	0.94	0.87	0.78	0.88

II

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.85
inat_disturb					0.76	0.85
inat_status				0.89	0.76	0.86
inat_access			0.92	0.89	0.75	0.84
inat_1km		0.9	0.94	0.89	0.76	0.85
inat	0.96	0.91	0.94	0.9	0.76	0.86

III

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.82
inat_disturb					0.66	0.79
inat_status				0.86	0.66	0.77
inat_access			0.89	0.87	0.64	0.76
inat_1km		0.83	0.89	0.83	0.69	0.77
inat	0.93	0.87	0.92	0.87	0.7	0.8

IV

	inat_1km	inat_access	inat_status	inat_disturb	agency	combined
agency						0.85
inat_disturb					0.67	0.78
inat_status				0.85	0.71	0.81
inat_access			0.89	0.83	0.66	0.77
inat_1km		0.83	0.91	0.84	0.68	0.78
inat	0.94	0.88	0.94	0.87	0.69	0.8

Figure B2 continued

Similarity or overlap (pairwise Schoener's *D* index) between (a) *Hedychium gardnerianum*, (b) *Lantana camara*, (c) *Leucaena leucocephala*, and (d) *Psidium cattleianum* model series within each site class, where 0 signifies no overlap and 1 is complete overlap.

(c) *Leucaena leucocephala*

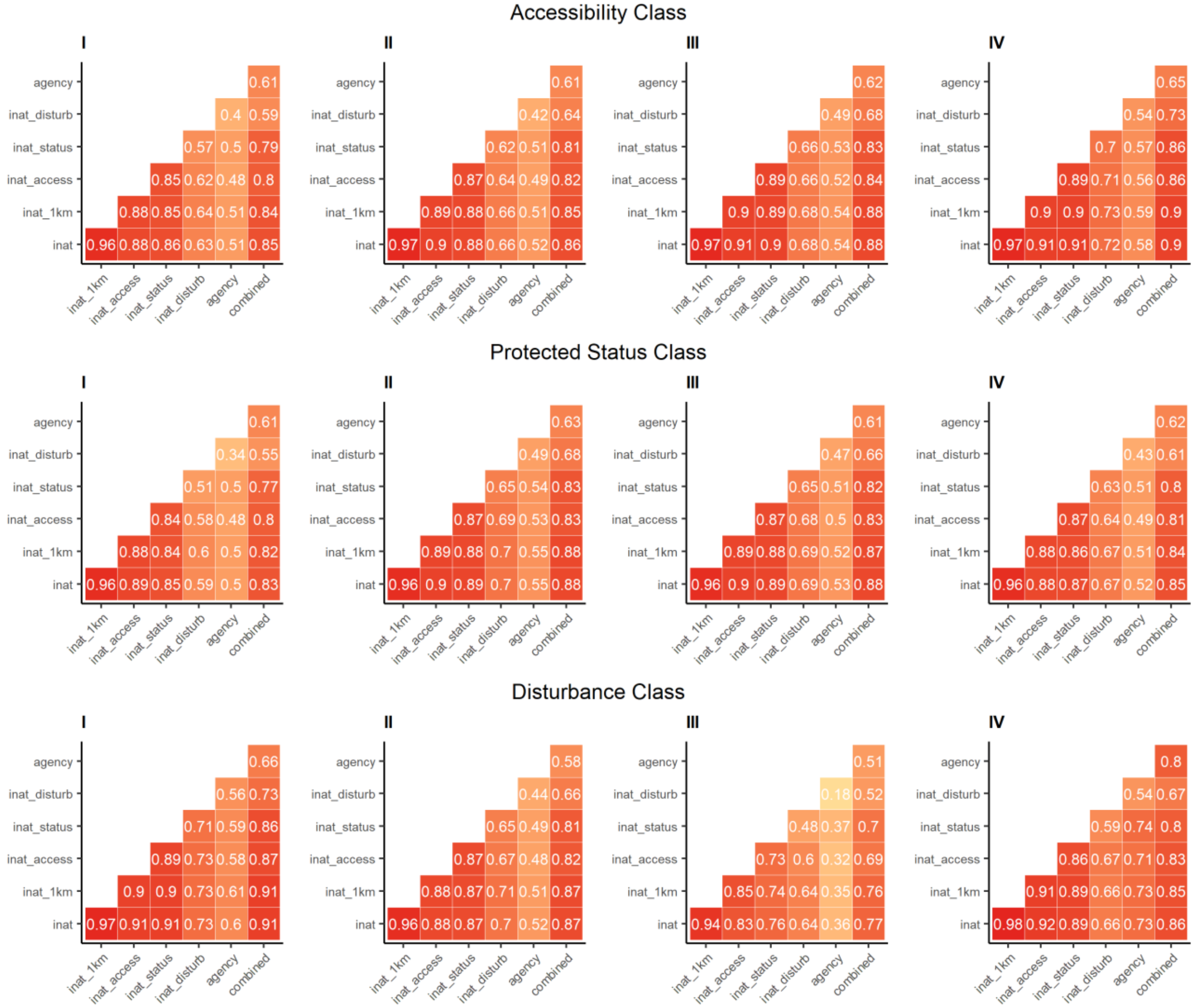


Figure B2 continued

Similarity or overlap (pairwise Schoener's *D* index) between (a) *Hedychium gardnerianum*, (b) *Lantana camara*, (c) *Leucaena leucocephala*, and (d) *Psidium cattleianum* model series within each site class, where 0 signifies no overlap and 1 is complete overlap.

(d) *Psidium cattleianum*

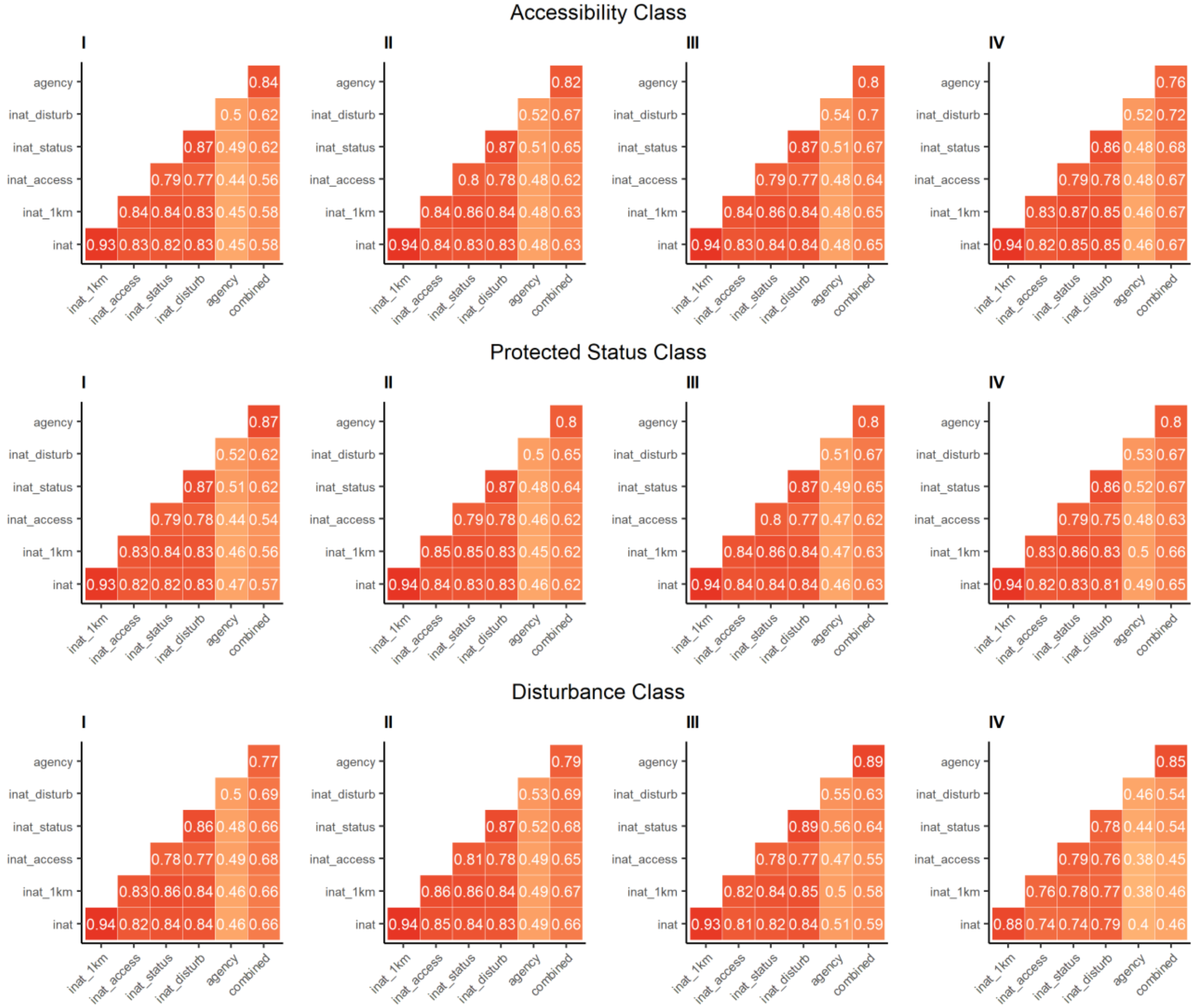


Figure B2 continued

Similarity or overlap (pairwise Schoener's *D* index) between (a) *Hedychium gardnerianum*, (b) *Lantana camara*, (c) *Leucaena leucocephala*, and (d) *Psidium cattleianum* model series within each site class, where 0 signifies no overlap and 1 is complete overlap.

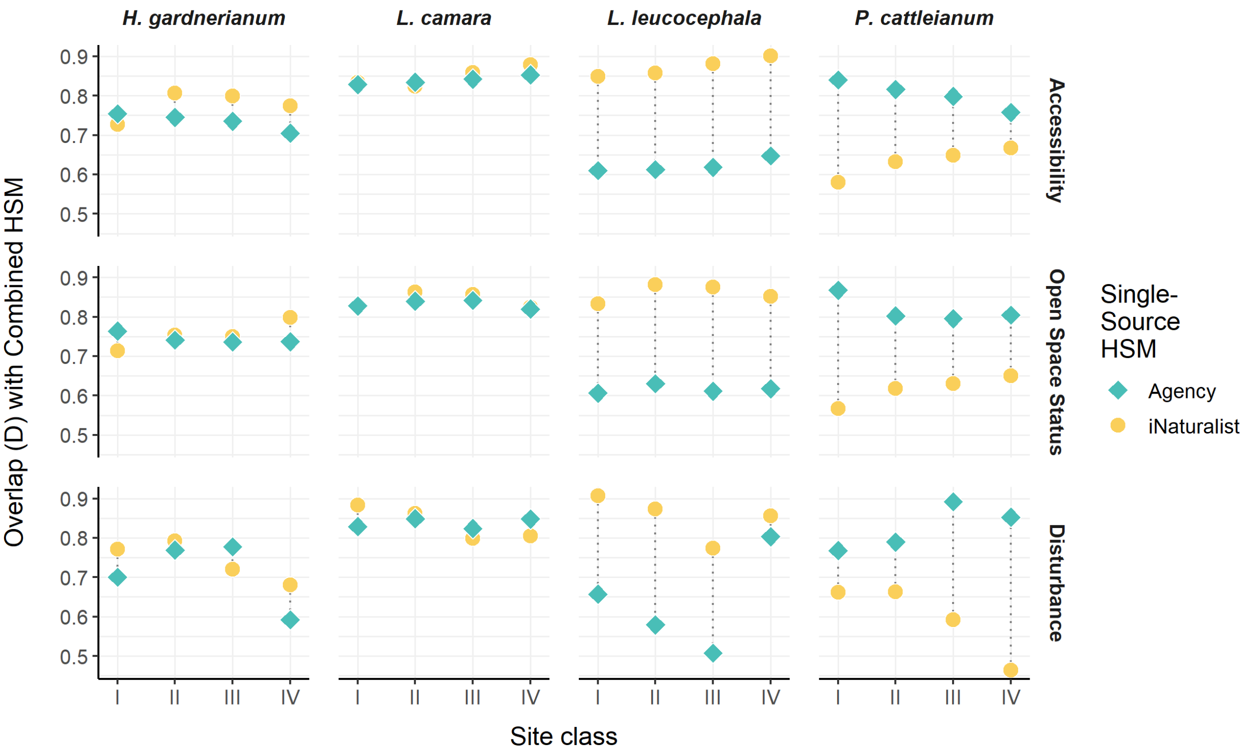


Figure B3

Similarity or overlap (pairwise Schoener's *D* index) between single-source habitat suitability models (iNaturalist- and agency-only) and the combined model, calculated within site classes.

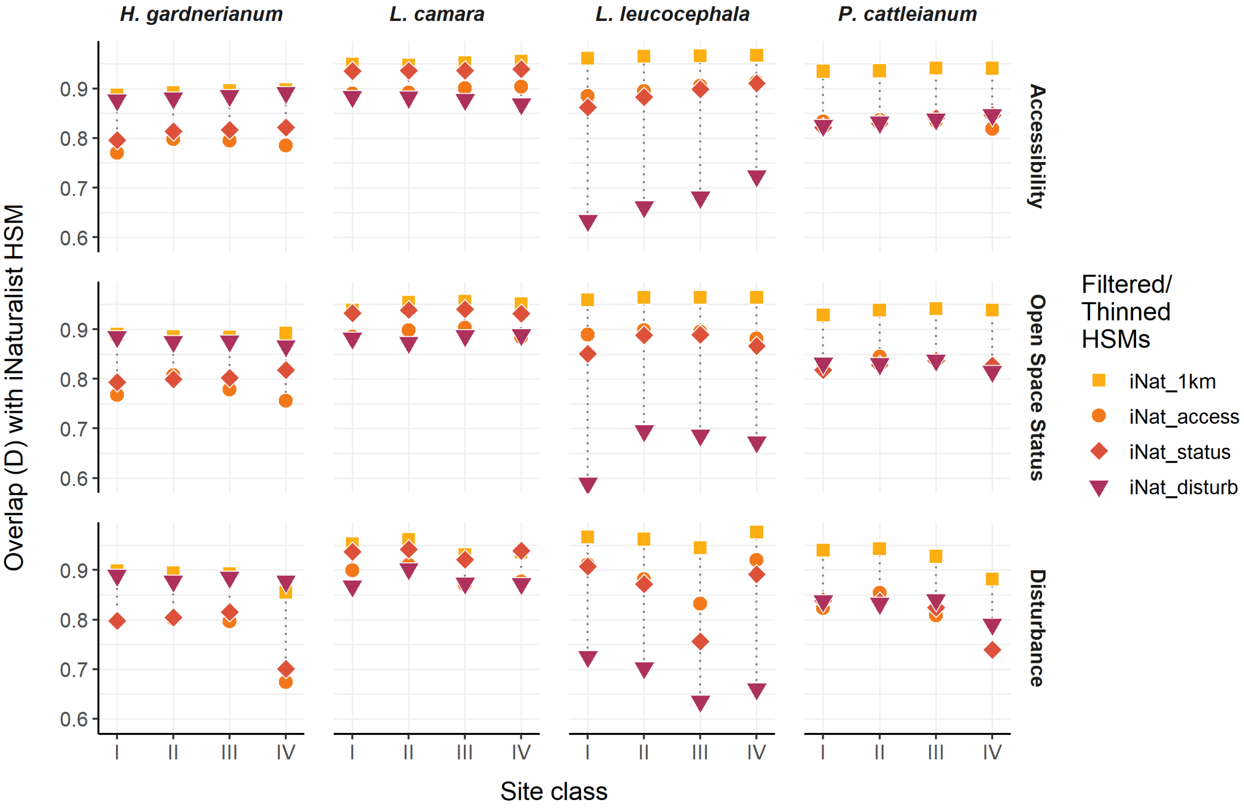


Figure B4

Similarity or overlap (pairwise Schoener's *D* index) between filtered/thinned iNaturalist habitat suitability models and the unfiltered iNaturalist model of each study species, calculated within site classes.

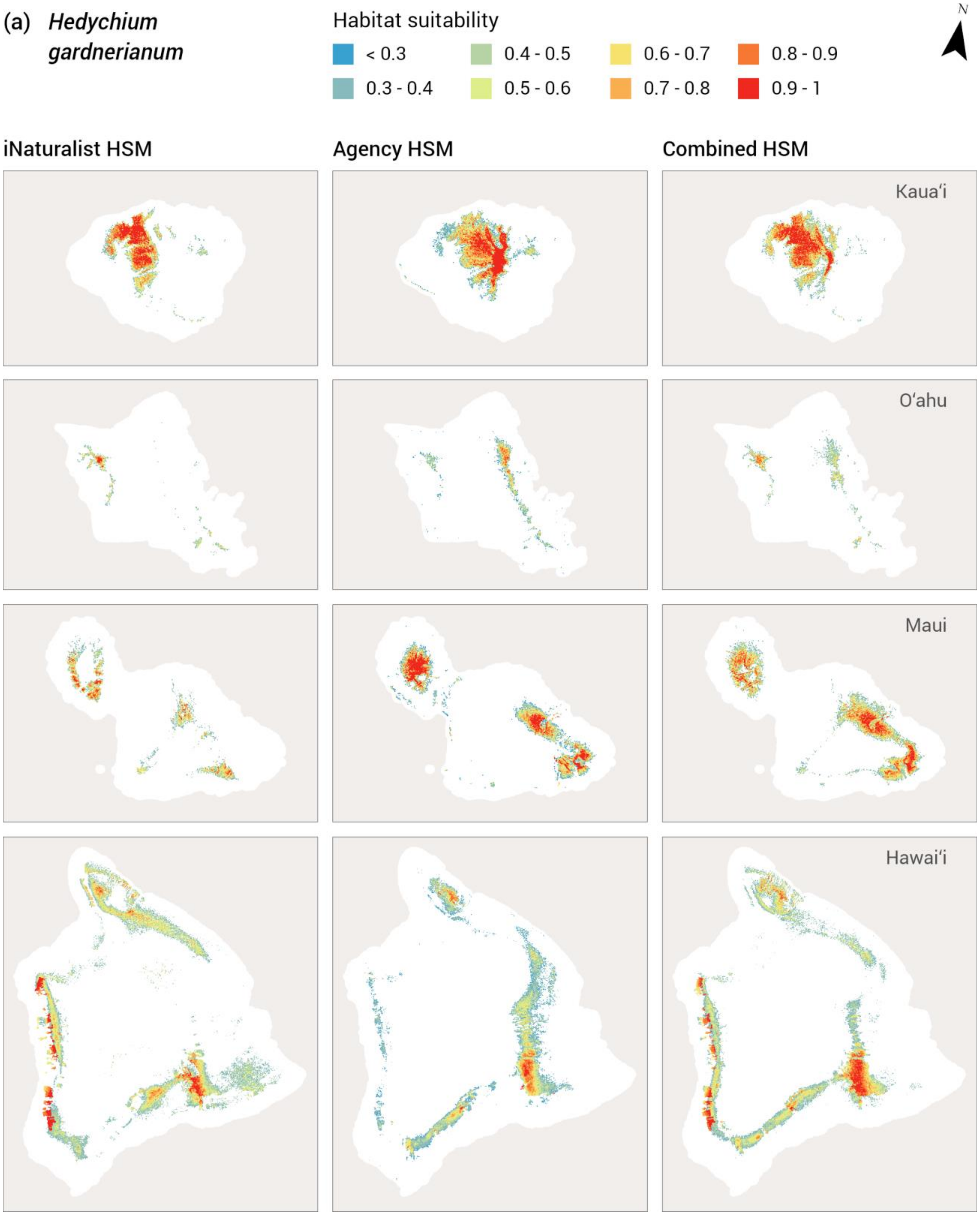


Figure B5

Habitat suitability predicted by iNaturalist unfiltered, agency, and combined models for (a) *Hedychium gardnerianum*, (b) *Lantana camara*, (c) *Leucaena leucocephala*, and (d) *Psidium cattleianum*. Unsuitable areas (cells below the maximum sum of sensitivity and specificity threshold) shown in white.

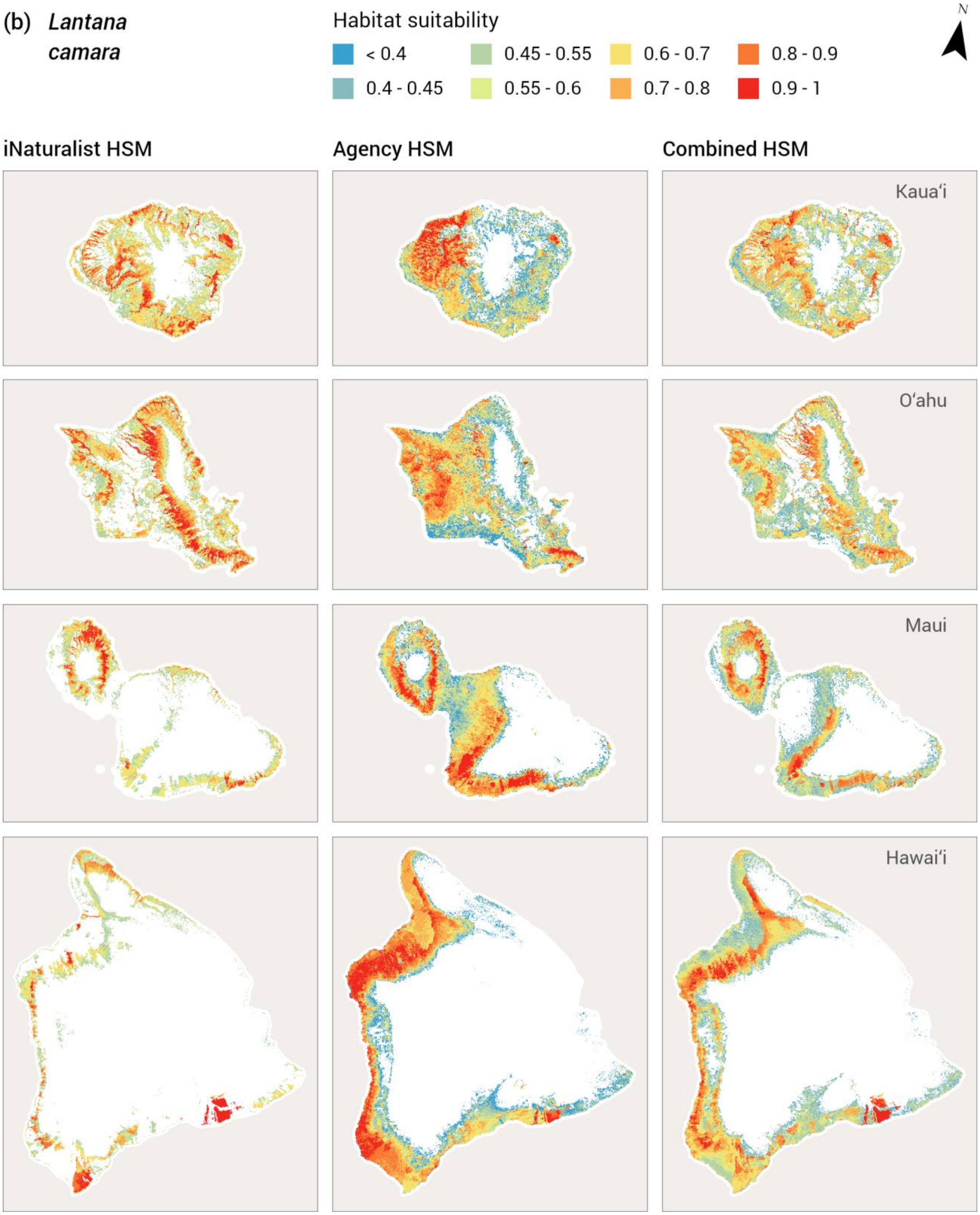


Figure B5 continued

Habitat suitability predicted by iNaturalist unfiltered, agency, and combined models for (a) *Hedychium gardnerianum,* (b) *Lantana camara*, (c) *Leucaena leucocephala,* and (d) *Psidium cattleianum*. Unsuitable areas (cells below the maximum sum of sensitivity and specificity threshold) shown in white.

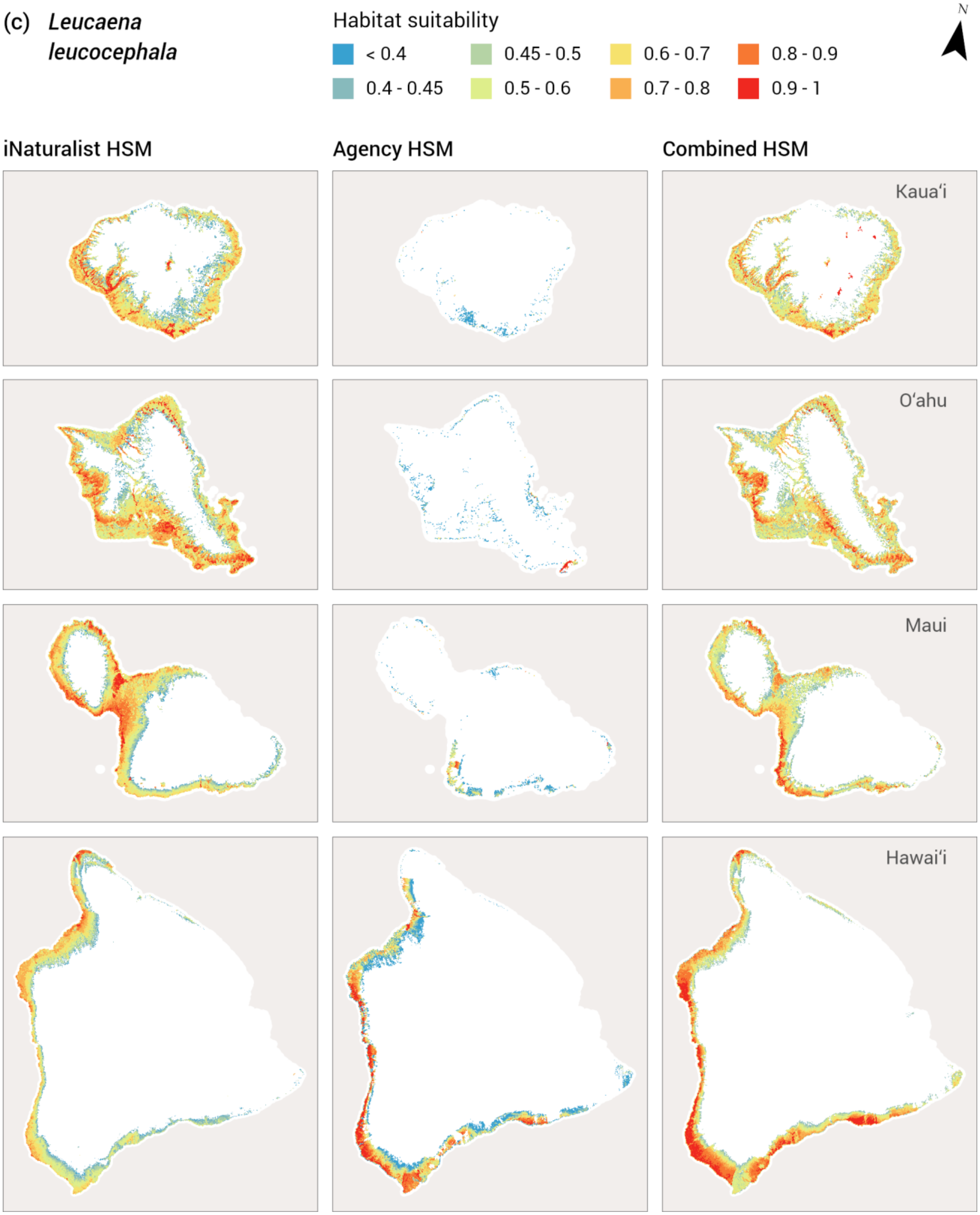


Figure B5 continued

Habitat suitability predicted by iNaturalist unfiltered, agency, and combined models for (a) *Hedychium gardnerianum*, (b) *Lantana camara*, (c) *Leucaena leucocephala*, and (d) *Psidium cattleianum*. Unsuitable areas (cells below the maximum sum of sensitivity and specificity threshold) shown in white.

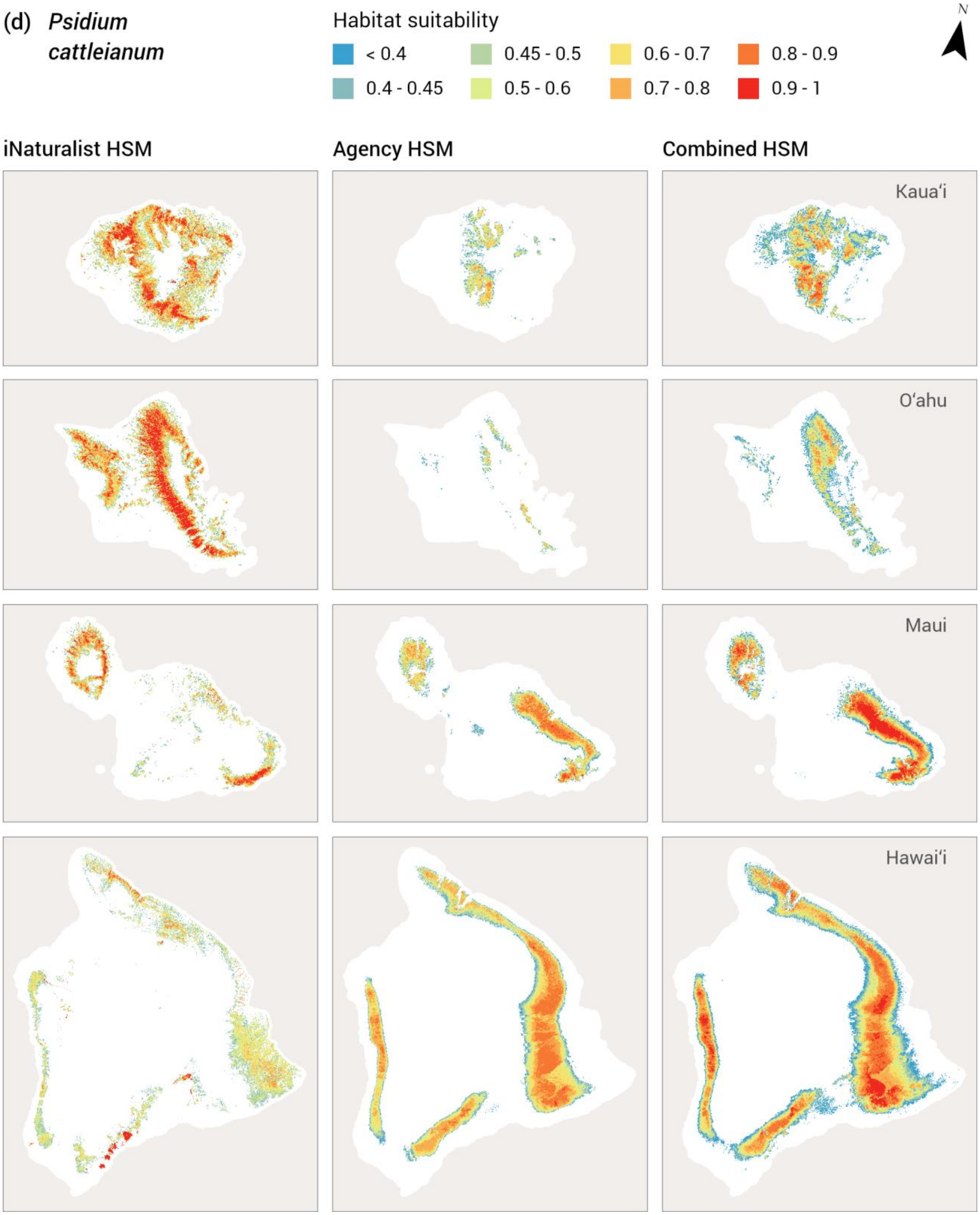


Figure B5 continued

Habitat suitability predicted by iNaturalist unfiltered, agency, and combined models for (a) *Hedychium gardnerianum,* (b) *Lantana camara*, (c) *Leucaena leucocephala,* and (d) *Psidium cattleianum*. Unsuitable areas (cells below the maximum sum of sensitivity and specificity threshold) shown in white.

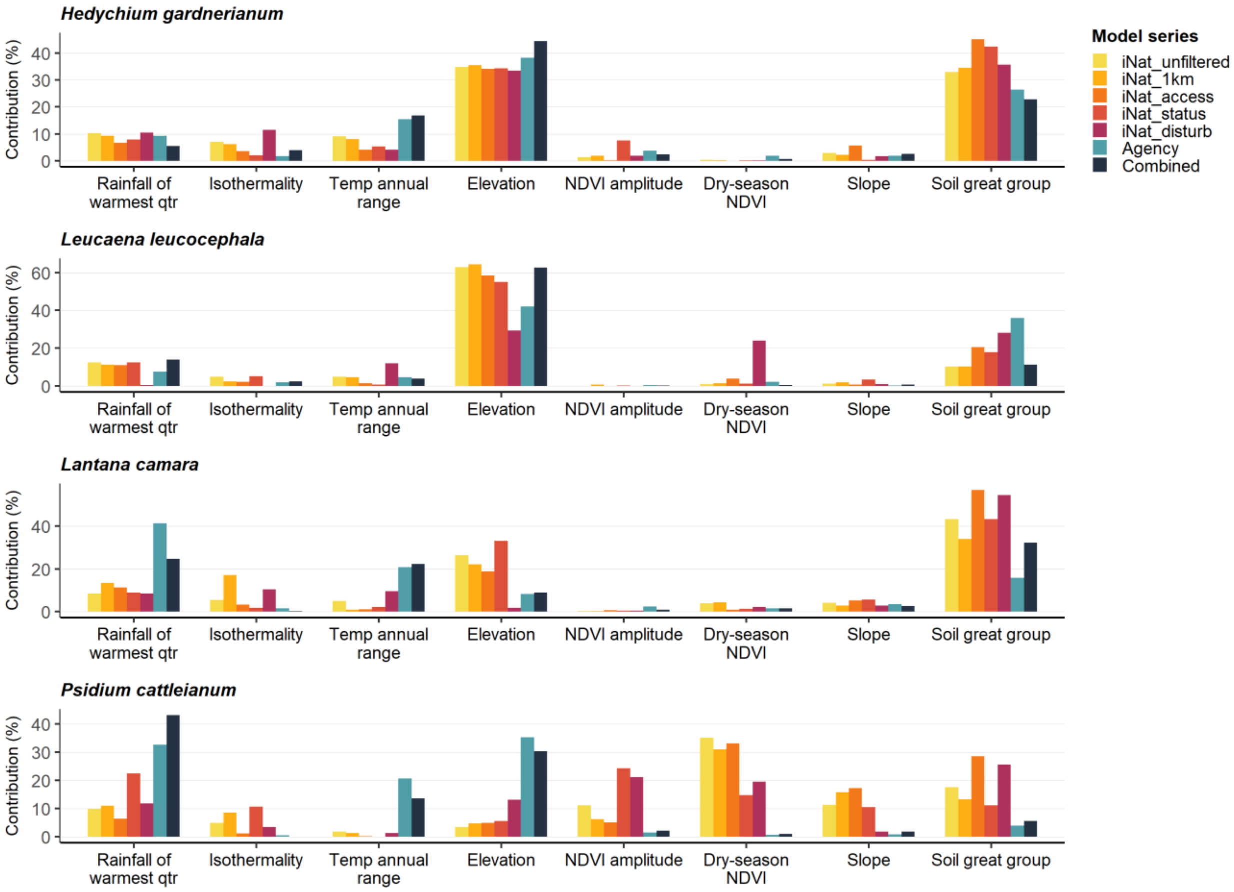
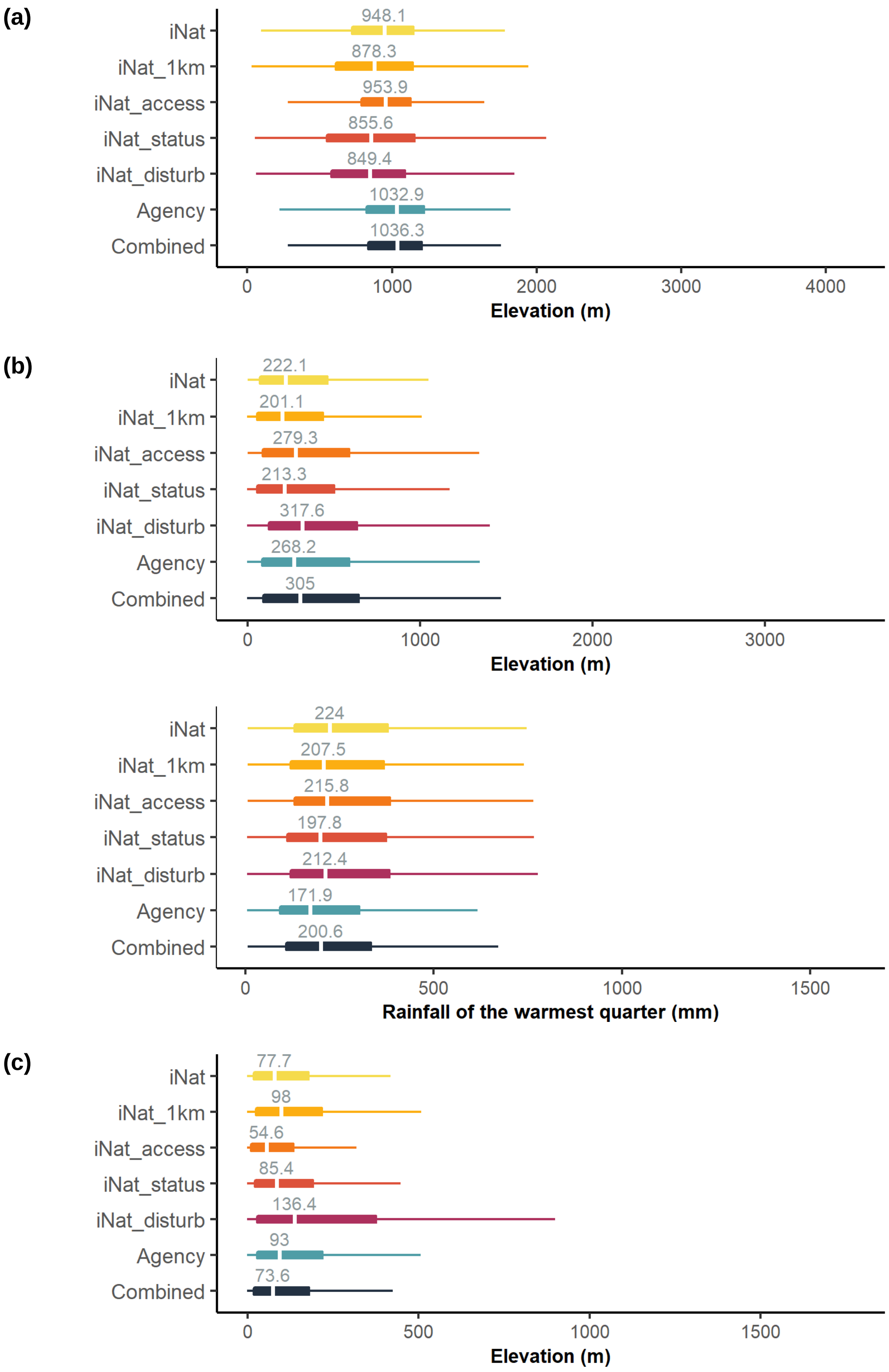


Figure B6

Percent contribution of predictors (excluding aspect and precipitation seasonality, which contributed less than 15% to any model) to each habitat suitability model.


(a)
iNat
iNat_1km
iNat_access
iNat_status
iNat_disturb
Agency
Combined
948.1
878.3
953.9
855.6
849.4
1032.9
1036.3
0
1000
2000
3000
4000
Elevation (m)
(b)
iNat
iNat_1km
iNat_access
iNat_status
iNat_disturb
Agency
Combined
222.1
201.1
279.3
213.3
317.6
268.2
305
0
1000
2000
3000
Elevation (m)
iNat
iNat_1km
iNat_access
iNat_status
iNat_disturb
Agency
Combined
224
207.5
215.8
197.8
212.4
171.9
200.6
0
500
1000
1500
Rainfall of the warmest quarter (mm)
(c)
iNat
iNat_1km
iNat_access
iNat_status
iNat_disturb
Agency
Combined
77.7
98
54.6
85.4
136.4
93
73.6
0
500
1000
1500
Elevation (m)

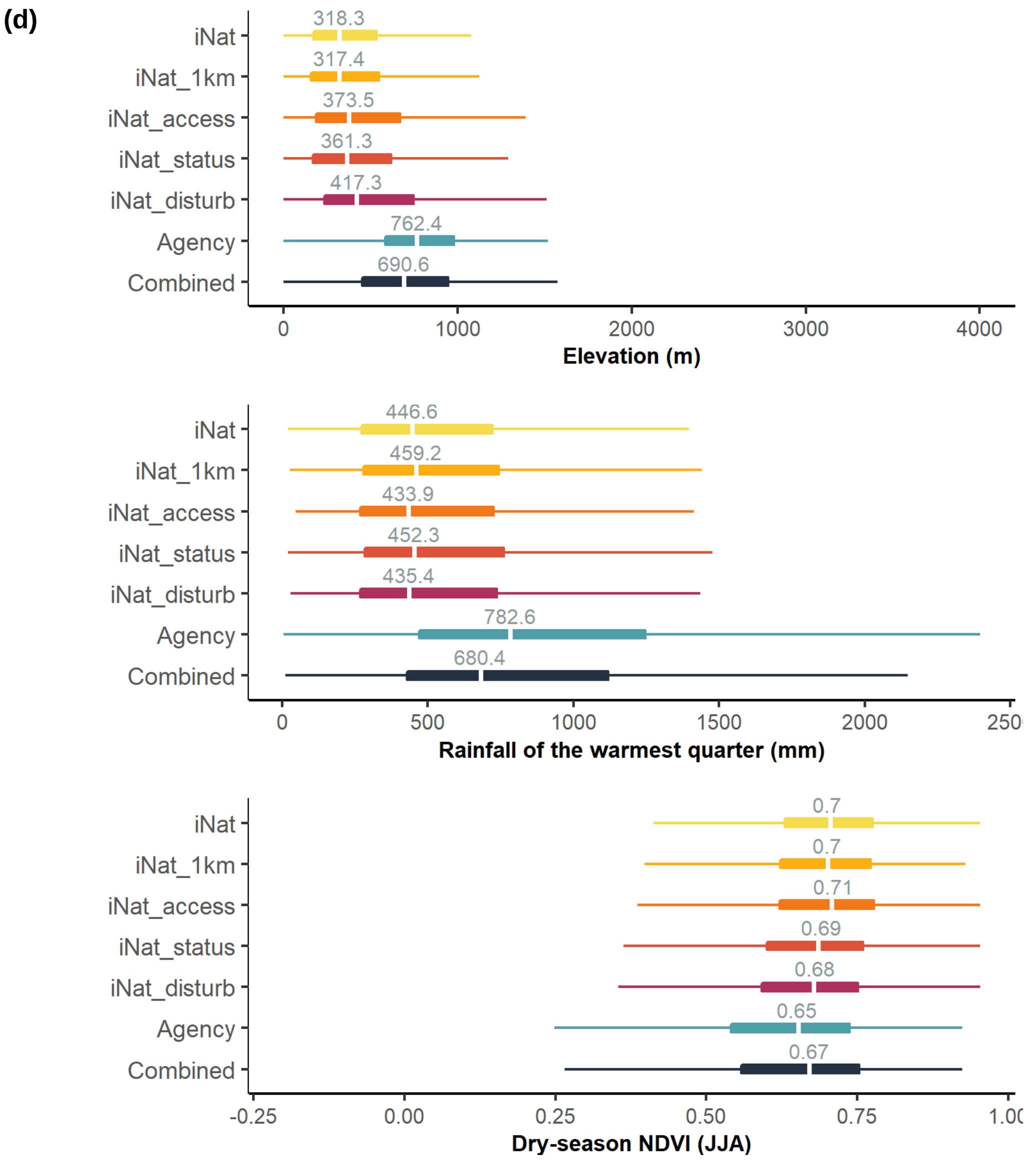


Figure B7

Range of values predicted suitable for the top continuous predictor of (a) *Hedychium gardnerianum*, (b) *Lantana camara*, (c) *Leucaena leucocephala*, and (d) *Psdium cattleianum.* Median labeled in gray, outliers removed from plot.

Appendix C

Supplementary Material for Chapter 4. Monitoring native and restored tropical dry forests with Landsat NDVI time series.

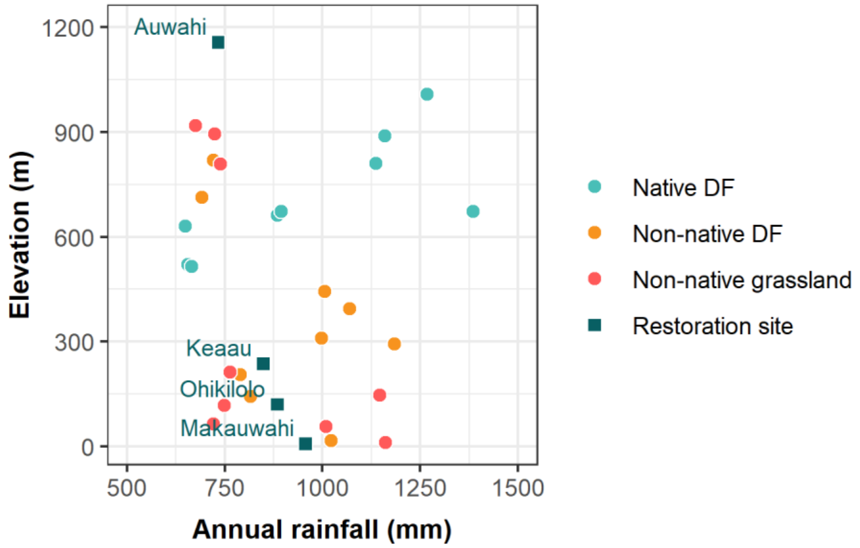


Figure C1

Elevation and annual rainfall characteristics of the dry forest (DF) and grassland sites.

Table C1

Results of Wilcoxon rank sum tests comparing seasonal median NDVI and RCV of NDVI within each vegetation class or restoration site (pre- and post-restoration for Keaau, Makauwahi, and Ohikilolo) over the full 1999-2022 series. *p*-values shown for significant results only.

		Median NDVI			RCV of NDVI		
	Season	FMA	MJJ	ASO	FMA	MJJ	ASO
Native dry forest	MJJ	<.05			--		
	ASO	<.05	--		<.01	<.01	
	NDJ	--	<.01	<.01	--	--	<.01
Non-native dry forest	MJJ	--			--		
	ASO	--	--		--	<.05	
	NDJ	<.01	<.001	<.001	--	--	<.05
Non-native grassland	MJJ	<.001			<.05		
	ASO	<.001	<.05		<.001	<.001	
	NDJ	<.01	<.001	<.001	--	<.01	<.001
Auwahi	MJJ	<.001			<.001		
	ASO	<.001	--		<.05	<.001	
	NDJ	<.001	--	--	<.001	<.001	<.001
Keaau Pre-restoration	MJJ	<.01			<0.05		
	ASO	<.01	--		<0.05	--	
	NDJ	<.01	<.01	<.01	--	<0.05	<0.05
Keaau Post-restoration	MJJ	<.01			--		
	ASO	<.01	<.01		--	--	
	NDJ	--	<.01	<.01	--	--	--
Makauwahi Pre-restoration	MJJ	--			<.05		
	ASO	<.01	--		<.001	--	
	NDJ	<.01	--	--	<.01	--	--
Makauwahi Post-restoration	MJJ	<.01			<.05		
	ASO	<.01	--		<.01	--	
	NDJ	<.001	<.001	<.001	--	<.01	<.01
Ohikilolo Pre-restoration	MJJ	<.001			--		
	ASO	<.001	<.001		--	--	
	NDJ	<0.05	<.001	<.001	--	--	--
Ohikilolo Post-restoration	MJJ	<.001	--	--	<.001	--	--
	ASO	<.001	--	--	<.001	<.01	--
	NDJ	<0.05	<.001	<.001	--	<0.05	<.001

Table C2

Change in pixel-wise NDVI parameters after restoration at Makauwahi, Ohikilolo, and Keaau. *p*-values shown for significant increases (blue) and decreases (orange) as determined by Wilcoxon rank sum tests. Pre- and post-restoration periods determined by the year that native outplanting began.

	Median NDVI				RCV of NDVI			
Season	FMA	MJJ	ASO	NDJ	FMA	MJJ	ASO	NDJ
Makauwahi	< 0.05	< 0.05	< 0.01	< .001	< .001	< .001	< .001	< .001
Ohikilolo	< 0.05	< 0.01	< .001	--	--	--	< 0.05	--
Keaau	--	< 0.05	--	< 0.05	--	< 0.05	< 0.05	--

Table C3

Seasonal median NDVI (and interquartile range) and RCV of NDVI of each study site, calculated over the 1999-2022 study period.

		Median NDVI (IQR)				RCV of NDVI			
	Site	FMA	MJJ	ASO	NDJ	FMA	MJJ	ASO	MDJ
Native dry forest	Waianae	0.83 (0.06)	0.81 (0.06)	0.81 (0.08)	0.84 (0.07)	0.06	0.06	0.07	0.05
	Nanakuli	0.81 (0.05)	0.8 (0.05)	0.81 (0.05)	0.82 (0.04)	0.05	0.05	0.04	0.04
	Kokee-1	0.78 (0.08)	0.77 (0.06)	0.77 (0.09)	0.8 (0.09)	0.07	0.06	0.09	0.08
	Kokee-2	0.78 (0.06)	0.76 (0.08)	0.78 (0.05)	0.8 (0.06)	0.06	0.08	0.05	0.05
	Manuka-1	0.77 (0.16)	0.74 (0.08)	0.69 (0.23)	0.8 (0.15)	0.15	0.08	0.26	0.12
	Kanepuu-1	0.77 (0.13)	0.72 (0.13)	0.67 (0.2)	0.74 (0.16)	0.10	0.11	0.21	0.16
	Kanepuu-2	0.68 (0.15)	0.64 (0.16)	0.56 (0.17)	0.64 (0.19)	0.13	0.17	0.22	0.20
	Manuka-2	0.66 (0.14)	0.59 (0.08)	0.61 (0.19)	0.7 (0.14)	0.12	0.11	0.24	0.14
	Kanaio	0.49 (0.16)	0.41 (0.13)	0.4 (0.12)	0.48 (0.14)	0.23	0.24	0.23	0.23
Non-native dry forest	Hanapepe	0.86 (0.06)	0.87 (0.04)	0.89 (0.04)	0.91 (0.03)	0.04	0.04	0.03	0.02
	Kuaokala	0.85 (0.07)	0.83 (0.09)	0.85 (0.08)	0.86 (0.07)	0.06	0.08	0.07	0.06
	Mokihana	0.84 (0.08)	0.79 (0.07)	0.78 (0.09)	0.88 (0.06)	0.07	0.06	0.08	0.04
	Kailua-1	0.82 (0.15)	0.85 (0.08)	0.87 (0.1)	0.83 (0.11)	0.12	0.07	0.08	0.10
	Kalaoa	0.79 (0.1)	0.8 (0.09)	0.79 (0.1)	0.81 (0.09)	0.09	0.06	0.10	0.08
	Keokea	0.76 (0.14)	0.72 (0.18)	0.62 (0.26)	0.81 (0.17)	0.12	0.14	0.31	0.13
	Lualualei	0.71 (0.2)	0.54 (0.23)	0.52 (0.25)	0.75 (0.23)	0.20	0.30	0.35	0.18
	South Point-1	0.71 (0.2)	0.57 (0.19)	0.51 (0.32)	0.76 (0.22)	0.20	0.24	0.38	0.20
	Kanaio Rd	0.71 (0.19)	0.69 (0.19)	0.69 (0.24)	0.81 (0.17)	0.19	0.20	0.21	0.12
Non-native grassland	Kalaheo	0.72 (0.14)	0.66 (0.18)	0.67 (0.2)	0.78 (0.12)	0.14	0.20	0.21	0.09
	Kailua-2	0.7 (0.24)	0.52 (0.24)	0.53 (0.3)	0.77 (0.23)	0.23	0.35	0.42	0.16
	Piilani Hwy	0.67 (0.22)	0.55 (0.25)	0.44 (0.39)	0.76 (0.23)	0.24	0.35	0.59	0.17
	Kula Hwy	0.67 (0.15)	0.63 (0.14)	0.61 (0.26)	0.71 (0.22)	0.15	0.16	0.32	0.19
	Kapaa Byp	0.61 (0.17)	0.55 (0.16)	0.51 (0.19)	0.69 (0.17)	0.21	0.20	0.25	0.18
	South Point-2	0.58 (0.33)	0.42 (0.21)	0.36 (0.25)	0.65 (0.35)	0.43	0.34	0.45	0.37
	Waimea	0.55 (0.25)	0.39 (0.25)	0.32 (0.19)	0.53 (0.31)	0.33	0.49	0.41	0.42
	Makaha	0.42 (0.27)	0.29 (0.14)	0.26 (0.16)	0.43 (0.28)	0.48	0.36	0.36	0.47
	Pohakuloa	0.39 (0.13)	0.35 (0.18)	0.32 (0.19)	0.43 (0.18)	0.25	0.39	0.42	0.31
Restoration	Keaau	0.69 (0.14)	0.49 (0.19)	0.46 (0.23)	0.7 (0.21)	0.15	0.28	0.36	0.21
	Makauwahi	0.67 (0.19)	0.6 (0.21)	0.58 (0.25)	0.72 (0.24)	0.19	0.25	0.32	0.21
	Auwahi	0.62 (0.16)	0.69 (0.13)	0.66 (0.22)	0.67 (0.16)	0.20	0.13	0.22	0.16
	Ohikilolo	0.6 (0.17)	0.41 (0.17)	0.38 (0.22)	0.67 (0.2)	0.20	0.30	0.42	0.21

Table C4

Kendall rank correlation coefficients of seasonal long-term (PA$_t$) and cumulative precipitation anomalies (CPA$_t$) from 1978-2019. Orange shading = statistically significant negative relationships (*$p < 0.05$, **$p < 0.01$).

		PAt				CPAt			
	Site	FMA	MJJ	ASO	NDJ	FMA	MJJ	ASO	NDJ
Native dry forest	Waianae	-0.09	-0.21 *	-0.08	-0.2	-0.16	-0.37 *	-0.15	-0.29
	Kanaio	-0.03	-0.03	0.06	-0.2	-0.08	-0.08	0.04	-0.25 *
	Kanepuu-1	0.03	0.07	-0.02	-0.17	0.01	-0.02	-0.07	-0.23
	Kanepuu-2	0.03	0.05	-0.02	-0.17	0	-0.05	-0.07	-0.23
	Kokee-1	0.01	-0.07	-0.07	-0.17	-0.02	-0.09	-0.11	-0.25
	Kokee-2	0.13	-0.04	0.01	-0.1	0.11	0.01	0	-0.14
	Manuka-1	-0.19	-0.32 **	-0.19	-0.15	-0.32 *	-0.52 **	-0.23	-0.27
	Manuka-2	-0.19	-0.31 **	-0.19	-0.16	-0.32	-0.52 **	-0.23	-0.26
	Nanakuli	0.06	-0.07	-0.03	-0.13	0.06	-0.06	-0.15	-0.23
Non-native dry forest	Mokihana	0.14	-0.03	-0.05	-0.09	0.14	-0.17	-0.13	-0.13
	Hanapepe	0.08	-0.07	0	-0.05	0.14	-0.13	-0.05	-0.1
	Kuaokala	-0.1	-0.17	-0.07	-0.24 *	-0.16	-0.3	-0.17	-0.32
	Lualualei	0.06	-0.01	-0.06	-0.14	0.08	-0.05	-0.2	-0.24
	Keokea	0.02	0.06	0.14	-0.22 *	-0.01	-0.02	0.2	-0.26
	Kanaio Rd	-0.05	-0.06	0.01	-0.18	-0.1	-0.12	0.06	-0.27
	Kalaoa	-0.23 *	-0.15	-0.14	-0.15	-0.27	-0.23	-0.19	-0.25
	Kailua	-0.19	-0.12	-0.09	-0.15	-0.23	-0.2	-0.16	-0.21
	South Point	-0.05	0.01	-0.12	-0.17	-0.12	-0.1	-0.11	-0.22
Non-native grassland	Kapaa Byp	0.09	-0.12	-0.13	-0.08	0.07	-0.18	-0.2	-0.18
	Kalaheo	0.08	-0.09	0.01	-0.02	0.13	-0.15	-0.04	-0.07
	Makaha	-0.05	-0.11	-0.12	-0.17	-0.07	-0.23	-0.22	-0.24
	Kailua	-0.01	-0.19	-0.04	-0.17	-0.09	-0.3	-0.09	-0.27
	Kula Hwy	-0.01	-0.01	0.09	-0.2	-0.03	0	0.13	-0.28
	Piilani Hwy	-0.09	-0.26 *	0.08	-0.12	-0.13	-0.29	0.06	-0.2
	Waimea	-0.02	0.05	0.21	-0.08	-0.08	0.1	0.2	-0.14
	Pohakuloa	-0.13	-0.02	0	-0.23 *	-0.2	-0.1	-0.06	-0.35 *
	South Point	-0.07	-0.01	-0.13	-0.17	-0.15	-0.15	-0.1	-0.21
Restoration site	Auwahi	-0.01	0.01	0.02	-0.21 *	-0.05	0.01	0.06	-0.27
	Keaau	-0.07	-0.16	-0.11	-0.18	-0.12	-0.3	-0.22	-0.26
	Makauwahi	0.02	-0.21	-0.13	-0.09	0.08	-0.26	-0.17	-0.18
	Ohikilolo	-0.14	-0.24 *	-0.11	-0.21 *	-0.2	-0.34 *	-0.22	-0.3

Table C5

Spearman correlation coefficient and statistical significance (**p* < 0.05, ***p* < 0.01, ****p* < 0.001) between PA_t and CPA_t and median NDVI from 1999-2019. Blue/orange shading = significant positive/negative relationships.

		PA_t × median NDVI				CPA_t × median NDVI			
	Site	FMA	MJJ	ASO	NDJ	FMA	MJJ	ASO	NDJ
Native dry forest	Waianae	0.04	0.53 *	0.28	-0.32	-0.15	0.52	0.14	-0.61 **
	Kanaio	0.81 ***	0.43	0.65 **	0.16	0.75 ***	0.6 **	0.49 *	0.18
	Kanepuu-1	0.38	0.36	0.65 **	-0.11	0.51 *	0.57 *	0.56 *	0.02
	Kanepuu-2	0.59 *	0.46	0.47 *	0.15	0.69 **	0.61 **	0.35	0.27
	Kokee-1	0.24	0.32	0.57 **	0.21	0.4	0.42	0.63 **	0.4
	Kokee-2	0.3	0.29	0.52 *	-0.02	0.29	0.39	0.58 *	0.17
	Manuka-1	0.07	-0.57	0.05	-0.21	0.17	-0.25	-0.11	-0.31
	Manuka-2	-0.09	-0.45	0.19	-0.06	0.14	-0.23	0.18	-0.01
	Nanakuli	0.26	0.21	0.29	0.1	0.06	0.14	0.1	0.38
Non-native dry forest	Mokihana	0.15	0.33	0.48 *	0.18	0.07	0.41	0.62 **	0.05
	Hanapepe	0.41	0.81 ***	0.49 *	-0.26	0.29	0.66 **	0.43	-0.05
	Kuaokala	-0.06	0.37	0.1	-0.14	-0.01	0.26	0.19	-0.09
	Lualualei	0.5 *	0.57 *	0.34	0.26	0.32	0.26	0.48 *	0.2
	Keokea	0.71 ***	0.61 *	0.36	0.05	0.62 **	0.8 ***	0.52 *	-0.01
	Kanaio Rd	0.59 **	0.32	0.58 **	0.02	0.67 **	0.61 **	0.6 **	-0.12
	Kalaoa	0.36	0.34	0.44	0.13	0.34	0.36	0.36	-0.11
	Kailua	0.38	0.2	0.45	0.01	0.36	0.09	0.63 **	-0.18
	South Point	0.53 *	0.36	0.53 *	0.26	0.42	0.44	0.65 **	0.29
Non-native grassland	Kapaa Byp	0.13	0.64 **	0.71 ***	0.46 *	0.4	0.51 *	0.58 **	0.36
	Kalaheo	0.49 *	0.73 ***	0.69 ***	0.08	0.32	0.47 *	0.51 *	-0.13
	Makaha	0.79 ***	0.53 *	0.47 *	0.44 *	0.6 **	0.43	0.42	0.1
	Kailua	0.68 **	0.34	0.71 ***	0.51 *	0.48 *	0.46 *	0.49 *	0.25
	Kula Hwy	0.74 ***	0.67 **	0.69 **	0.08	0.67 **	0.67 **	0.64 **	-0.09
	Piilani Hwy	0.52 *	0.06	0.78 ***	0.44 *	0.4	0.26	0.66 **	0.2
	Waimea	0.42	0.38	0.56 **	0.59 **	0.38	0.5 *	0.59 **	0.33
	Pohakuloa	0.6 **	0.54 *	0.61 **	-0.17	0.42	0.25	0.62 **	-0.61 **
	South Point	0.54 *	0.33	0.65 **	0.59 **	0.39	0.41	0.65 **	0.32
Restoration site	Auwahi	0.42	0.3	0.59 *	-0.22	0.45	0.46	0.58 *	-0.18
	Keaau	0.78 ***	0.33	0.27	0.58 **	0.61 **	0.07	0.36	0.35
	Makauwahi	0.51 *	0.77 ***	0.61 **	0.18	0.41	0.59 **	0.49 *	-0.26
	Ohikilolo	0.27	0.67 **	0.52 *	0.39	0.48 *	0.41	0.59 **	0.05

Table C6

Spearman correlation coefficient and statistical significance ($*p < 0.05$, $**p < 0.01$, $***p < 0.001$) between PA_t and CPA_t and RCV of NDVI from 1999-2019. Blue/orange shading = significant positive/negative relationships.

		PA_t × RCV of NDVI				CPA_t × RCV of NDVI			
	Site	FMA	MJJ	ASO	NDJ	FMA	MJJ	ASO	NDJ
Native dry forest	Waianae	0.43	0.12	0.21	0.22	0.33	0.21	0.31	0.29
	Kanaio	-0.18	0.02	-0.11	0.1	0.01	0.08	0.07	-0.26
	Kanepuu-1	-0.24	0.26	0.26	0.36	-0.27	0.18	0.31	0.21
	Kanepuu-2	-0.35	-0.3	-0.01	-0.17	-0.26	-0.26	0.13	-0.23
	Kokee-1	0.22	0.21	-0.04	-0.17	0.1	0.27	0.01	-0.44 *
	Kokee-2	0.04	-0.17	-0.4	-0.08	0.04	0.1	-0.56 *	0.02
	Manuka-1	0.18	0.15	0.23	0.22	0.31	0.72 *	0.19	0.27
	Manuka-2	-0.34	-0.5	-0.08	-0.18	-0.13	-0.22	-0.29	-0.31
	Nanakuli	-0.04	0.14	-0.25	0.37	-0.04	0.26	-0.36	0.13
Non-native dry forest	Mokihana	-0.13	-0.17	-0.04	-0.64 **	-0.16	-0.12	-0.34	-0.49 *
	Hanapepe	-0.28	0.03	-0.25	-0.05	-0.32	-0.16	-0.1	0.1
	Kuaokala	-0.04	-0.16	-0.01	0.01	-0.21	0.13	0.19	-0.05
	Lualualei	-0.48 *	0.01	0.49 *	-0.06	-0.59 **	-0.01	0.42	-0.23
	Keokea	-0.29	-0.16	0.08	0.16	-0.27	-0.32	-0.05	-0.01
	Kanaio Rd	-0.22	-0.27	-0.23	0.02	-0.19	-0.14	-0.34	0.11
	Kalaoa	-0.62 **	0.45	-0.38	-0.14	-0.58 *	0.53	-0.3	0.03
	Kailua	-0.14	0.25	0.34	0	-0.05	0.06	0.03	0.18
	South Point	-0.2	0.22	-0.24	-0.17	-0.39	0.43	-0.07	-0.34
Non-native grassland	Kapaa Byp	0.28	0.24	0.21	-0.36	0.06	0.56 *	0.11	-0.23
	Kalaheo	-0.09	-0.58 **	-0.24	0.13	-0.15	-0.17	-0.12	0.14
	Makaha	0.05	0.59 **	0.53 *	-0.07	0.27	0.48 *	0.43	-0.12
	Kailua	-0.22	-0.17	0.28	-0.34	-0.2	-0.12	0.08	-0.23
	Kula Hwy	-0.28	0.23	-0.22	-0.08	-0.18	0.05	0.14	-0.28
	Piilani Hwy	-0.4	-0.05	-0.21	-0.34	-0.14	-0.24	-0.15	0.06
	Waimea	-0.29	-0.21	0.28	-0.31	-0.45	0.09	0.11	-0.32
	Pohakuloa	-0.12	-0.07	0.14	0.36	0.14	0.03	0.2	0.28
	South Point	-0.34	0.02	0.03	-0.63 **	-0.27	0.11	0.04	-0.44 *
Restoration site	Auwahi	-0.19	-0.21	-0.11	0.14	-0.3	-0.34	-0.08	-0.01
	Keaau	-0.27	0.01	0.64 **	-0.43	-0.11	0.29	0.54 *	-0.12
	Makauwahi	-0.44	-0.6 **	0.16	-0.1	-0.2	-0.34	-0.01	0.28
	Ohikilolo	-0.24	0	0.29	-0.14	-0.08	-0.03	0.22	0.27