A UAS-based approach toward habitat suitability modeling of a rare endemic plant

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Abstract

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Predicting habitat and mapping species distributions are important to address declining biodiversity and species extinctions. Habitat suitability models (HSM) predict potential habitat based on a species' ecological niche, demonstrating a valuable tool for recovery efforts. Many threatened and endangered species are limited in distribution and abundance, occurring in fragile habitats or in inaccessible locations, making them difficult to map through traditional field surveys. Conventional satellite and aerial remote sensing data also have limitations in mapping species due to a mismatch in the spatiotemporal scale of ecological processes. Unoccupied Aerial Systems (UAS) can address these limitations to adequately model habitat for these species of concern. In this study, the rare endemic plant *Hackelia venusta* (Showy

Stickseed) serves as a focal species to explore the role and utility of UAS in plant conservation. We predicted suitable habitat for *H. venusta* and compared HSMs built using UAS imagery with those built using traditional aerial and satellite imagery. We found that UAS models performed marginally better than models using aerial imagery, and both UAS and aerial models outperformed satellite imagery. The primary advantages provided by UAS include targeted acquisitions of high resolution (<10 cm/pixel) data, temporal discretion, and flexibility of sensor types. The growing use of UAS in environmental monitoring makes them an integral tool for future conservation applications.

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Chapter 1: General Introduction

This Thesis project initially began with a question, is it possible monitor plants with drones? More precisely, can rare herbaceous plants be identified and quantified using data collected from unoccupied aerial systems (UAS)? Conservation of rare plants is critical for maintaining and promoting ecological processes, species richness and biodiversity, and improving resiliency to climate change and anthropogenic pressures (Cerrejón et al., 2021; Leitão et al., 2016; Mouillot et al., 2013). Identifying where rare species occur can be a difficult task due to low occurrences across a broad range, narrowly endemic populations within a small range, or due to biased or incomplete geographic information (Guisan et al., 2006; Lomba et al., 2010; MacKenzie et al., 2005). Additionally, remote terrain and challenging access, as well as limitations in human, time and funding resources make field studies difficult to unfeasible (Le Lay et al., 2010; Turner et al., 2003).

Remote sensing techniques have been widely used to overcome limitations to field-based data collection to map environmental metrics and ecological phenomena at global scales including direct observations of organisms, species assemblages, land cover classification, change detection, and indirect approaches used to infer biotic and abiotic processes (Andrew et al., 2014; Gamon et al., 2007; Kerr & Ostrovsky 2003; Wang et al., 2010). Early remote sensing applications in ecology, biodiversity, and conservation used geographic information systems (GIS), species distributions, biological variables, and vegetation maps derived from satellite imagery (e.g., Landsat) to generate maps used for biodiversity gap analysis (McKendry & Machlis, 1991; Prendergast et al., 1999; Scott et al., 1993). The advancement of remote sensing in ecology and conservation through the 1990s saw increased applications in producing thematic datasets, landcover and terrain mapping, vegetation and habitat characterization, temporal dynamics, ecological modeling, and more (Cohen & Goward, 2004; Turner et al., 2003).

Current applications in ecology using aerial and satellite remote sensing data include measuring leaf area index (Zheng & Moskal, 2009); characterization of vegetation and forest canopy structure (Chen et al., 2003; Selkowitz et al., 2012); species abundance and habitat mapping; estimation of evapotranspiration, productivity, biomass, and carbon; soil characterization, and disturbance monitoring (Andrew et al., 2014; Lausch et al., 2016). Even with the rapid growth in sensor types and computing power, aerial and satellite based remote sensing data still have limitations to match the spatial and temporal scale of ecological processes and phenomena required for many applications and studies (Müllerová et al., 2017). Unoccupied aerial vehicles (UAV) offer several ways to overcome these limitations (Cruzan et al., 2016), providing a new platform for remote sensing applications in ecology.

Recent research has demonstrated the ability of UAS to aid in identification of larger trees and shrubs (Fletcher & Erskine, 2012; Hernandez-Santin et al., 2019; Lobo Torres et al., 2020; Sankey et al., 2018; Torres-Sánchez et al., 2018), and classification of vegetation types and forest canopy characterization (Alonzo et al., 2018; Komárek et al., 2018; Michez et al., 2016; Wallace et al., 2016), but limited research has explored UAS applications specifically for plant conservation (Baena et al., 2018). Several recent studies have explored the use of high-resolution (<10 cm/pixel) imagery derived from UAS for plant census and identification (Landenberger et al., 2003; Leduc & Knudby, 2018; Rominger & Meyer, 2019), with varying success. Cerrejón et al. (2021) provide a current literature review of 43 remote sensing studies to detect rare plants, which includes UAS case studies as well as conventional forms of airborne and satellite remote sensing data, and found both direct and indirect remote sensing approaches had great potential for detection and prediction of rare plants. With the rapid pace of UAS and sensor technology development (Yao et al., 2019), it is likely there will be an equivalent growth of publications and research in plant conservation applications.

In addition to plant conservation, there is considerable interest around UAS applications in monitoring invasive plant species. A recent review by Dash et al. (2019) found 23 published studies, from 2016 to the time of their study, which used UAS to monitor invasive plants, with a growing trend commensurate with that of conventional airborne and satellite remote sensing studies of invasive plants. Müllerová et al. (2017) found an important advantage of UAS imagery over satellites was flexible data acquisition, targeted return periods and the ability to target a species' phenological stage when detecting invasive plants. UAS applications to monitor plant invasions will certainly be a growing area of interest for land and resource managers as limitations to data processing and flight regulations are reduced over time (Colomina & Molina, 2014).

Of course, UAS applications in plant ecology and conservation represent a small slice of applied research for this rapidly developing technology, with widespread adoption in various fields of environmental monitoring. A special issue of UAS for environmental applications in the International Journal of Remote Sensing (Simic Milas et al., 2018) highlights the rapid advances in the field, including applications in vegetation mapping, agricultural purposes, geomorphologic applications, river water quality mapping, and animal tracking. Singh & Frazier (2017) found that most published studies involving terrestrial applications of UAS focused on agriculture, geomorphology, forestry, and civil engineering. A review of UAS applications in environmental monitoring by Manfreda et al. (2018) corroborates Dash's review, showing a near exponential increase in published articles since the 1990's based on a search of the ISI Web of Knowledge [now Web of Science] using keywords "UAS", "UAV", and "environment".

Many other reviews on UAS applications have been published recently, including wetland mapping and hydrological modeling (Jeziorska, 2019), surveying wild animals (Wang et al., 2019), agroforestry (Pádua et al., 2017), precision agriculture (Hassler & Baysal-Gurel, 2019; Maes & Steppe, 2019; Tsouros et al., 2019), and current monitoring practices using UAS (Tmušić et al., 2020). It is clear from these meta-analyses and reviews that UAS are increasingly becoming a standard tool for acquiring remote sensing data for environmental monitoring and a wide variety of other applications.

The study presented in Chapter 2 builds upon this growing body of research, directly applying a UAS-based approach toward plant conservation. This study is a collaboration between the Washington Rare Plant Care and Conservation (Rare Care) program and the Remote Sensing and Geospatial Analysis Laboratory (RSGAL) within the School of Environmental and Forest Sciences at the University of Washington. The Rare Care program, in addition to managing a robust citizen science rare plant monitoring program, seed collection and storage, engages in interagency efforts for plant conservation and research. One such endeavor is the recovery effort for the rare endemic plant *Hackelia venusta* (showy stickseed), which has been the subject of ongoing research and conservation activity as well as previous thesis studies (Vance, 2013). An initial hope of this study was to use UAS to identify and monitor individual plants for a remote sensing-based plant census. However, due to technical and logistical issues on top of the global COVID-19 pandemic, we were unable to collect sufficient data, including low altitude UAS flights, with high enough pixel resolution to discern individual plants. Nonetheless, we were able to capture UAS data to model and predict potential habitat for future *H. venusta* outplanting areas, as will be explained in further detail in Chapter 2.

The overarching objective of this study was to explore ways in which UAS can be used in plant conservation. The interagency recovery team involved with *H. venusta* conservation efforts was also curious in how UAS could be used to address recovery plan objectives, and to address challenges presented by the rugged inaccessible terrain in which *H. venusta* grows. Through a remote sensing-based workflow, we developed a plan to identify potential locations with suitable habitat, perform UAS flights, and deliver high resolution (< 10cm/pixel) imagery to the stakeholders for use in monitoring and analysis.

In addition to exploring a UAS application for plant conservation more broadly, this thesis provides a case study using UAS remote sensing data as an input to habitat suitability models (HSM). HSMs and species distribution models (SDMs) extrapolate species distribution data in space and time, typically based on a statistical model, and represent a class of the most widely used models in ecology and conservation (Elith & Leathwick, 2009; Franklin, 2010; Guisan & Thuiller, 2005; Guisan et al., 2017). The increasing availability of species occurrence and geoinformation data, along with software packages and computing power have facilitated rapid growth and widespread adoption of these models for research and management decisions (Fletcher et al., 2019; Zurell et al., 2020). Most recently, several individual models are commonly combined, averaged or ensembled to improve species distribution and habitat suitability predictions (Araújo & New, 2007; Hao et al., 2019; Le Lay et al., 2010; Marmion et al., 2009). This study followed the ensemble approach to generate more robust predictions for suitable habitat.

Common applications of HSMs and SDMs include reserve design and conservation planning; impact assessment and resource management; ecological restoration and ecological modeling; risk and impacts of invasive species and pathogens; and effects of global warming on biodiversity and ecosystems (Franklin, 2010). While models usually predict biotic distributions, such as species occurrence, suitable habitat, or land cover class, abiotic environmental factors are also commonly mapped or predicted using a similar approach (Ferrier, 2002). Hirzel & Le Lay (2008), in a review of HSMs linked to ecological niche theory, found that most HSM-based studies address the ecological niche issues of a single species (e.g., niche characteristics, variable selection, response curves) rather than niche interactions (e.g., competition, predation, mutualism, parasitism), communities (e.g., multi-species, species richness), or niche evolution (e.g., habitat-dependent fitness, taxonomic separation). This highlights a gap in research, where conservation focused HSMs could yield greater contributions to environmental and resource management.

Summarizing a review by Peterson (2006), Hirzel & Le Lay outline key management implications and conservation applications of HSMs linked to niche theory, including delineating ecological requirements of species and their limiting factors; understanding biogeography and dispersal barriers; finding unknown populations and new species; identification of reintroduction sites; design of conservation plans and reserves; prediction of habitat loss and effects; anticipation of species invasions; and prediction of climate change effects. The study presented in this thesis primarily applies a model to identify reintroduction sites, driven by known ecological requirements.

Austin (2002) stresses the importance of the relationship between ecological theory and method to develop a better modeling strategy. Using a niche-based approach, many studies have demonstrated the need for understanding and incorporating ecological processes to improve conservation focused HSMs (D'Amen et al., 2017; Guisan et al., 2013; Jetz et al., 2019; Saupe et al., 2012), particularly for rare species (Edwards et al., 2005; Fois et al., 2018; Guisan et al., 2006; Williams et al., 2009). Furthermore, studies have shown that an ensemble approach can aid in modeling for rare species (Breiner et al., 2015; Breiner et al., 2018; Lomba et al., 2010). Other approaches to improve HSMs focus on incorporating remote sensing data (Andrew & Ustin, 2009; Arenas-Castro et al., 2019; Cord et al., 2013; Leitão & Santos, 2019). Using remotely sensed data derived from UAS in HSMs is a natural progression in the exploration of improving modeling approaches. In our efforts to identify suitable habitat for the rare endemic plant *H. venusta*, we used an ensemble HSM approach based on ecological drivers, incorporating UAS-based remote sensing data into a predictive model. The following is a result of that effort.

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Chapter 2: A UAS-based approach toward habitat suitability modeling of a rare endemic plant

1. Introduction

1.1. Background

Species conservation plays a critical role in maintaining healthy ecosystem services for current and future generations (Carey, 1998; Thompson & Angelstam, 1999). Rare plant species play an especially critical role in maintaining ecological processes, species richness and biodiversity, and improving resiliency to climate change and anthropogenic pressures (Cerrejón et al., 2021; Leitão et al., 2016; Mouillot et al., 2013). Conservation biologists have spent several decades tackling the problem of declining biodiversity and species extinction across the globe (Schemske et al., 1994). To effectively achieve conservation goals and reach benchmarks for species recovery, consistent monitoring must occur at multiple scales and be integrated with regional management plans (Angelstam et al., 2004; Busch & Trexler, 2003; Nichols & Williams, 2006). Successfully identifying suitable reintroduction sites is often a necessary step to meet delisting criteria and achieve self-sustaining populations. Additionally, a baseline understanding of species distribution, habitat requirements, threats, and trends must be established to drive management actions toward recovery. In recent decades, there has been a sizable increase in the development and use of modeling techniques to better map and understand species distributions, their environmental requirements, and forecast change (Zurell et al., 2020). Species habitat mapping and modeling is typically accomplished using a suite of input variables including ecosystem-functioning predictors (e.g., forest structure, above-ground biomass, leaf area, soil types), spectral indices, climate data, land cover classes, bioclimatic and topographic variables (Arenas-Castro et al., 2019).

A prediction of species distribution or habitat suitability is a geographical extrapolation of a species distribution model (SDM), which utilizes existing species occurrence data and environmental variables thought to influence habitat suitability (Elith & Leathwick, 2009; Franklin, 2010). Habitat suitability predictor variables derived from remote sensing data include land-use/land-cover classifications, topography, snow and water cover, spectral and textural indexes, and weather data (Andrew & Ustin, 2009). These data are often used to model and predict suitable habitat for one or more species of interest. Model results have important implications for research, conservation, management, and policy, utilized by stakeholders such as land and resource managers (Bradley, 2014; Jetz et al., 2019). In the case of threatened and endangered species, these models can help identify locations for reintroduction to increase population numbers and meet recovery objectives. Species distribution and habitat suitability modeling are comparable to terms such as "species niche model", "ecological niche model", or "bioclimatic envelope model", in which models are used to describe a fundamental or realized niche and the suitability of habitat to support a species (Franklin, 2010). For the purposes of this paper, we will primarily use the term habitat suitability model (HSM) to refer to this concept.

Remotely sensed predictor variables used in HSMs, such as traditional satellite and aerial based remote sensing platforms, are not always adequate for mapping and monitoring plant species and habitat distributions due to cost, resolution, and timing (Manfreda et al., 2018). While airborne and satellite-based remote sensing products have become increasingly used in ecology due to the free and publicly available nature of some data, such as the Landsat, Sentinel, and NAIP collections, several key limitations of many data sets persist including: 1) a high cost per scene for imagery at fine (1m or better) spatial resolution for rare or invasive species monitoring; 2) unsuitable revisit periods for nadir imagery; and 3) cloud and atmospheric interference (Loarie et al., 2007). These technologies present limitations in ecological research due to the mismatch between pixel resolution, timing of the acquisition, and the scale of many ecological processes, such as the phenological stage of plants (Anderson & Gaston, 2013). Otherwise, sub-meter resolution images from traditional remote sensing techniques, such as space-borne satellite platforms, may be cost-prohibitive (Koh & Wich, 2012). In addition, available imagery may not be cloud-free nor have been taken under conditions needed for analysis. Finally, while satellite archives may be extensive, they do not offer flexibility or discretion of when an acquisition will occur (Müllerová et al., 2017).

Unoccupied aerial systems (UAS) - typically referring to an unoccupied aerial vehicle, colloquially known as drones, with one or more attached sensors - may alleviate these issues by providing a relatively low-cost platform that can be deployed under ideal study conditions and repeated as necessary for continued monitoring. The low-flight altitude of UAS can provide higher spatial resolution data with low atmospheric interference, and the user may define the temporal resolution (Wing et al., 2013), providing scale-appropriate measurements of ecological phenomena (Anderson & Gaston, 2013). Another important element of UAS surveys is the ability to target specific phenological stages (e.g., flowering, leaf-on or -off conditions), when a given plant species may be most distinguishable from the surrounding environment in terms of spectral reflectance (Michez et al., 2016; Müllerová et al., 2017).

The use of UAS in research has grown rapidly in recent years (Colomina & Molina, 2014; Simic Milas et al., 2018), becoming a key new technology with applications in agriculture, geomorphology, forestry, civil engineering, rangeland, and wildlife studies (Singh & Frazier, 2018; Tmušić et al., 2020). Recent growth in UAS research includes monitoring invasive plant species, identification of trees and shrubs, monitoring vegetation indices in precision agriculture, and characterization of forest structure and type (Adão et al., 2017; Dash et al., 2019; Manfreda et al., 2018; Sankey et al., 2018). However, applications regarding plant conservation, particularly herbaceous plants, are largely absent from scientific literature (Baena et al., 2018; Rominger & Meyer, 2019). Furthermore, research involving the integration of UAS data, compared and contrasted with satellite and aerial data, in ecological modelling is underexplored (Wang et al., 2019). The high spatial resolution and temporal discretion of UAS-derived imagery may allow for more accurate mapping of potential habitat, enhancing long-term monitoring, and potentially revealing important ecological conditions associated with growth and establishment that can be used to further plant conservation.

The study described hereafter explores an application in which UAS can be used as a low-cost accessible and effective tool for plant conservation. We used the rare endemic plant *Hackelia venusta* (Showy Stickseed) as a focal species to explore the use of UAS to model and predict suitable habitat for reintroduction. Federally listed as an endangered species in 2002, *H. venusta* is restricted to one known population in Chelan County, Washington, and occurs on steep, rocky slopes with loose sandy soils prone to erosion. This study addresses recovery actions and downlisting criteria outlined in a 2007 Recovery Plan (USFWS, 2007) and subsequent 2019 Amendment, conducting investigations for suitable reintroduction sites to establish "at least three stable, self-sustaining populations … separated by at least 2 kilometers (1.2 miles) … through further inventory, or through reintroduction or augmentation" (USFWS, 2019) (p. 6). Currently, the single known *H. venusta* population is extremely vulnerable to a single a single stochastic event, such as mass wasting, which could wipe out the entire distribution of the listed species. Identifying new areas of suitable habitat addresses the need to establish new populations for redundancy and protection against catastrophic loss.

The surrounding region targeted for new establishment plantings of *H. venusta* consists of steep, rugged terrain with cliffs and boulders which make conventional field surveys extremely time and resource intensive (Le Lay et al., 2010; Turner et al., 2003). Identifying where rare species occur can be a difficult task due to low occurrences, narrowly endemic populations, or due to biased or incomplete geographic information (Guisan et al., 2006; Lomba et al., 2010; MacKenzie et al., 2005). Remote sensing techniques using air- and space-borne sensors have been widely established in the fields of ecology, biodiversity, and conservation to observe, collect, and model environmental metrics and ecological phenomena (Andrew et al., 2014; Turner et al., 2003; Wang et al., 2010). Despite recent advancements in sensor types and computing capability, aerial and satellite based remote sensing data still have limitations to match to the spatial and temporal scale of ecological processes required for many conservation applications and studies (Müllerová et al., 2017).

UAS have been shown to be an effective tool to overcome these spatiotemporal limitations. They can be used to generate habitat maps in sensitive habitats or in terrain that is difficult to access, and can be an affordable tool to monitor large expanses of land with low physical impacts (Cruzan et al., 2016; Rominger & Meyer, 2019). A UAS remote sensing-based approach to identify potential outplanting sites could offer a methodology to prioritize field excursions and refine a habitat suitability model, which could then be applied to larger or different spatial extents. Overall, UAS provide a tool for quick, repeatable low impact monitoring that can identify priorities for conservation and management (Manfreda et al., 2018).

Since *H. venusta*'s listing as a federally endangered species, an interagency recovery team was established, currently consisting of representatives from the US Fish and Wildlife Service (USFWS), USDA Forest Service (USFS), Washington State Department of Natural Resources (DNR) Natural Heritage Program, and the University of Washington Botanic Gardens (UWBG) Rare Plant Care and Conservation program. To date, numerous field surveys have been conducted to monitor *H. venusta* population numbers and distribution as well as to search for new unknown populations (Arnett, 2011; USFWS, 2007). Recent studies from the recovery team have developed a better understanding of habitat requirements, tree and shrub encroachment, soil characterization, and development of propagation and outplanting protocols (Gibble, 2015). This research effort aids directly in current and ongoing efforts toward establishing minimum viable population numbers for *H. venusta*.

1.2. Study aims and objectives

This study aims to advance the understanding of UAS technology in conservation and ecological applications, particularly for rare plant species and its aid in habitat suitability modeling. This goal is of critical interest to the interagency recovery team's objective for identifying suitable locations for outplanting sites to bolster population numbers. The specific objectives of this study are to:

1. Identify suitable habitat for *H. venusta* conservation and future reintroduction sites, through a remote sensing-based workflow to prioritize target survey areas for conservation activities.

2. Compare habitat suitability model predictions from UAS to aerial and satellite-derived models.

By addressing these objectives, we will demonstrate an applied workflow for prioritizing UAS survey areas and future field work for conservation managers and practitioners. This study addresses the gap in knowledge of UAS applications in plant conservation, and explores how very high spatial resolution (<10 cm) UAS imagery performs in habitat suitability models relative to other forms of traditional aerial and satellite-based imagery. While this study focused on a rare herbaceous plant, the methodology provides techniques and applications for use in a wide variety of other disciplines within conservation, resource management, and ecology. Additionally, through model evaluation and comparison, we validate previous research and existing literature using an ensemble model approach to improve HSM results.

Previous interagency recovery team field investigations identified a few potential reintroduction outplanting sites to meet recovery objectives, but steep and inaccessible terrain limited the ability to survey much of the region of interest. We address this limitation directly in Objective 1 of our study using a remote sensing-based approach to identify ouplanting sites, limiting impacts and total field visits. We developed a workflow to model suitable habitat using satellite imagery over a large extent which includes the core extant *H. venusta* population, yielding prioritized areas where we then flew UAS and acquired <10 cm resolution multispectral imagery. Based on previous studies and available literature, we hypothesized that UAS imagery would improve the accuracy of habitat suitability models relative to models using aerial and satellite imagery, primarily due to improvements in spatial resolution within targeted spatial extents. To test this hypothesis, addressing Objective 2, we flew UAS surveys over the smaller extent core *H. venusta* population and compared performance of models predicting suitable habitat using UAS imagery against publicly available NAIP (National Agriculture Imagery Program) aerial imagery and Sentinel-2 satellite imagery.

With the remote sensing-based workflow demonstrated here, endangered species recovery teams, land managers, conservation biologists, and other stakeholders can quickly deploy these techniques in their conservation efforts. This approach can be applied to other species of interest or concern (e.g., invasive plants, wildlife, fungi, or non-vascular plants) where spatially targeted high resolution optical data supports key ecological inference. Moreover, this workflow supports an iterative adaptive management strategy where habitat suitability modeling can be refined and extended to larger landscapes. The results from this study demonstrate the instrumental role UAS can provide in conservation, ecology, and beyond.

2. Materials and Methods

2.1. Focal species and study area

The rare, narrowly endemic plant Showy Stickseed, *Hackelia venusta* (Piper) St. John (Boraginaceae) occurs in dry, loose granitic sand and crevices among boulders and talus; restricted to sites with low vegetative cover from unstable slopes. It is a short herbaceous perennial, 2-4 dm tall, with showy white flowers (13-22 mm wide) which bloom May to early June. Ranked G1/S1 on the NatureServe Global Conservation Status Ranks, *H. venusta* is restricted to a single population of fewer than 500 plants, located in the Wenatchee Mountains of the Cascade Range in Chelan County, Washington. The known extant population currently includes a roughly 16-hectare (40 acre) area in Tumwater Canyon, occurring exclusively on USDA Forest Service (USFS) land.

Past field surveys have found *H. venusta* to occur in a mixed ponderosa pine (*Pinus ponderosa*) Douglas-fir (*Pseudotsuga menziesii*) forest type, near openings and rock outcroppings, at elevations between 472 meters (1,550 ft) to 823 meters (2,720 ft). Earlier studies have characterized habitat to include slopes averaging 24-34 degrees, aspects from 200-250 degrees, tree canopy cover 16-58%, low shrub cover, and presence of forbs combined with a low cover of grasses and sedges (Gibble, 2015). Soils have been characterized as shallow, relatively undeveloped, well-drained and coarse textured with low organic matter content, containing low nitrogen similar to soils in mixed conifer forests on decomposing granite. Extractable phosphorus is high, possibly due to mineralization of P from fires, or from inputs from volcanic ash (Vance, 2013). *H. venusta* commonly occurs with other herbaceous forbs including *Achillea millefolium, Cerastium arvense, Lupinus latifolius,* and *Penstemon pruinosus.* Understory shrubs (*Ceanothus velutinus, Spiraea betulifolia*) have been identified as an encroachment threat to viable habitat. Wildfires have played a role in maintaining open, sparsely vegetated sites, reducing competition from large woody shrubs. A 1994 fire in the site killed much of the understory vegetation and several trees but did not negatively impact *H. venusta* populations (USFWS, 2007). Additional identified threats include mass wasting, highway maintenance and construction (e.g., herbicide and road de-icer use), competition from noxious weeds, and shading (USFWS, 2019).

To satisfy Objective 1, we first established a larger area of interest (AOI) to search for *H. venusta* seedling outplanting sites, constrained to a 185 km^2 (72 mi^2) study area encompassing the known *H. venusta* population and surrounding lands within 11 km (7 mi). While the historic range is not currently known, this area was chosen by recovery team members and species experts to include suitable areas where this plant may be established within an acceptable range for conservation efforts. This larger extent AOI included sites identified from previous efforts as potential habitat and former outplantings in Tumwater and Icicle Creek canyons. To address Objective 2 and train an adequate predictive model, we chose a smaller 4-hectare AOI containing the core *H. venusta* population, in which we compared UAS to aerial and satellite data. Figure 1 below indicates the 185 km^2 larger AOI in the eastern slopes of the Cascade range, and shows the typical habitat in which *H. venusta* grows. The location of the core AOI is not explicitly shown due the sensitive nature of the endangered species and protect its' location information.

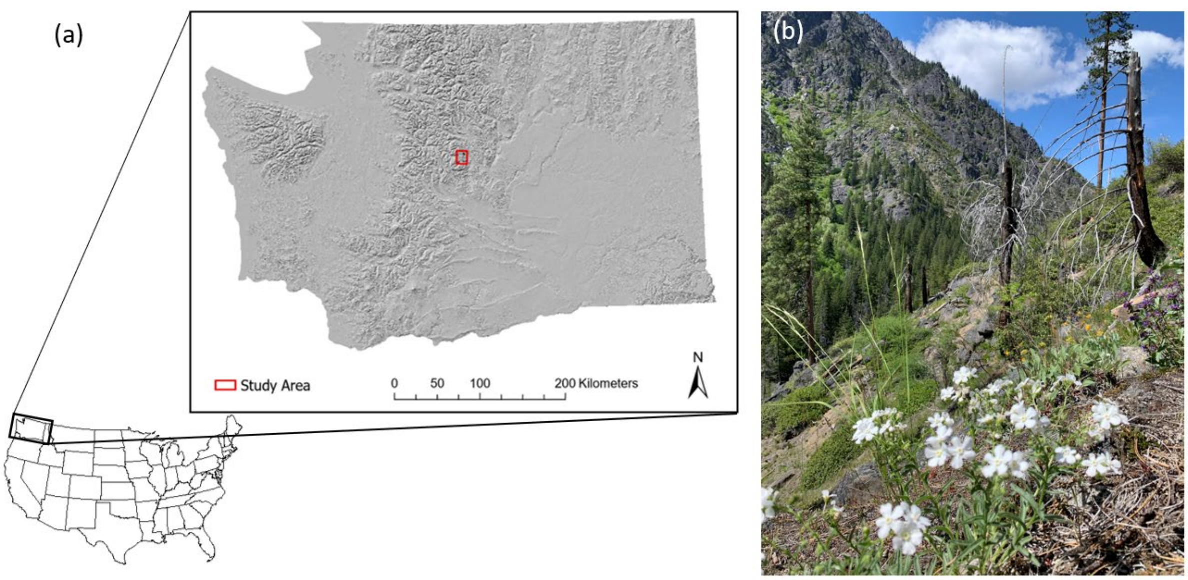


Figure 1. Study area showing: a) Location in Washington, USA. Red box represents the 185 km^2 AOI; and b) Showy stickseed in the foreground in typical habitat type.

2.2. Remote sensing-based workflow

We developed a remote sensing-based workflow to identify suitable habitat for *H. venusta* outplanting locations within the larger extent AOI. Figure 2 below shows the general workflow, beginning with a broad satellite-based model using known species occurrence data and environmental predictor variables (discussed in further detail below), producing a map to prioritize and execute UAS surveys. Data generated from UAS surveys was then processed and applied toward an HSM within the core AOI, producing prediction maps which were used to compare against predictions from aerial and satellite data. UAS data products and model predictions will be used for future field surveys and site visits focused on *H. venusta* reintroduction and can also be used to evaluate and refine model parameters. High resolution imagery from UAS surveys, and model predictions used for field surveys are valuable deliverables for the interagency recovery team. As environmental conditions and land management policies change, these can be adapted and refined, incorporated into an adaptive management approach for conservation purposes.

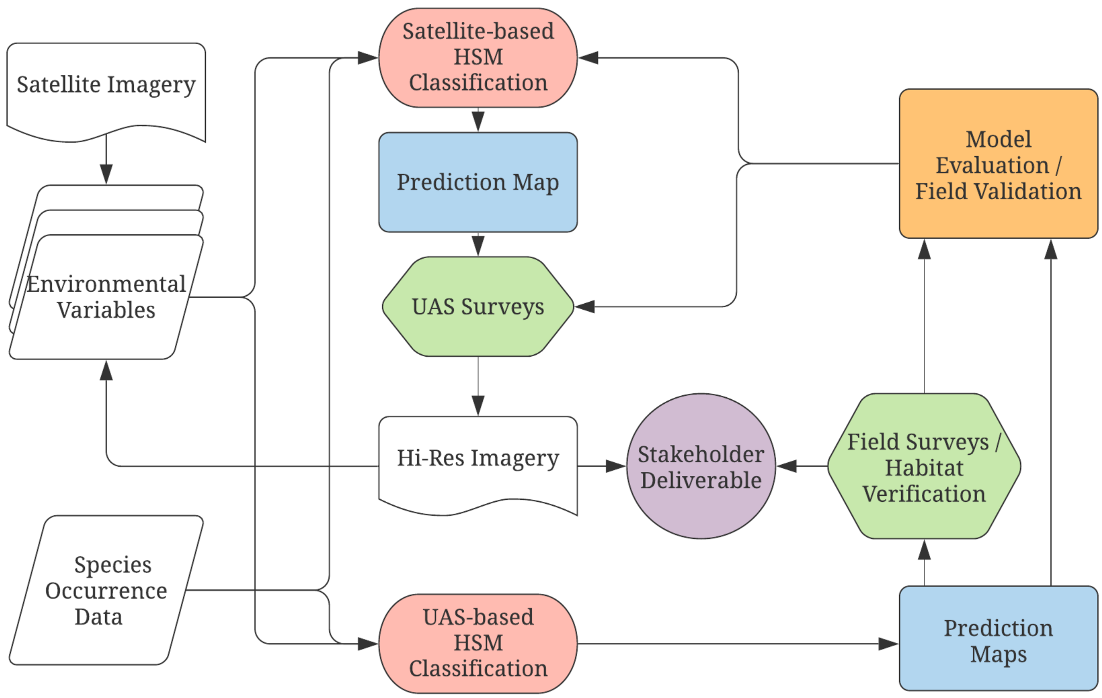


Figure 2. Modeling workflow used in this study.

2.3. UAS flights and image processing

The satellite-based classification yielded a binary presence/absence map for the larger extent AOI, which was used as a reference to prioritize potential sites with suitable *H. venusta* habitat for UAS surveys. These sites were evaluated visually using 1-meter resolution NAIP (National Agriculture Imagery Program, 2017) imagery – the most recently available imagery at the time of the study – by experts from the interagency recovery team (IRT). These were then prioritized for UAS flights based on a combination of expert recommendation and site access (constrained by proximity to roads and parking areas) for UAS take off/landing zones.

A two-person field crew visited the prioritized sites and narrowed down UAS survey areas based on take-off/landing locations where visual line of sight of the UAS could be maintained (per U.S. Federal Aviation Administration regulations). UAS flights were carried out above tree canopy at approximately 90 m (295 ft) above ground level (AGL) with 85% overlap, in June through September of 2020, which captured the core extant *H. venusta* population and areas within the larger extent AOI. Flights were performed within 2 hours before and after solar noon during weather conditions which permitted UAS flight. For these flights, we used a DJI Inspire 1 with stock camera (1/2.3" CMOS, 12.4 Megapixels, 94° FOV, 20mm f/2.8), and attached MicaSense RedEdge 3 multispectral camera (1280 x 960 px, 5.5 cm focal length, 47.2° FOV, Blue: 475 nm (20 nm bandwidth), Green: 560 (20), Red: 668 (10), Red edge: 717 (10), Near Infrared: 840 (40); MicaSense, Inc., Seattle, WA, USA).

Flights were programmed with the UgCS software (SPH Engineering, Latvia) using the photogrammetry tool for UAV land survey missions. A 91.4 cm (3 ft) resolution lidar-derived Digital Terrain Model was obtained from lidar acquisitions from 2015-2018 (*Washington Lidar Portal*) and imported into the software to enable programmed elevation changes, allowing the UAS to maintain consistent in-flight above ground altitude, thus resulting in a more consistent ground sampling distance (GSD) and spatial resolution. Due to the incredibly steep canyon terrain in the study area, this feature is essential for pre-programmed flights to maintain a level AGL and to avoid additional flights using a stratified survey strategy (Cruzan et al., 2016) (p. 3).

Imagery captured from both the stock DJI camera and MicaSense sensors were processed using Agisoft Metashape Professional (Agisoft, LLC, St. Petersburg, Russia) software. Images were processed to generate a dense point cloud (approx. 100 points/m^2), digital surface model (DSM), and high-resolution orthomosaic rasters (3.96 cm/pixel RGB; 6 cm/pixel multispectral), which were manually georeferenced to 30.5 cm (1 ft) resolution National Agriculture Imagery

Program (NAIP) imagery from 2019 in ArcGIS Pro (Esri, Redlands, CA, USA). This produced nine orthomosaics, covering approximately 148 hectares (365 acres), with ground sampling distances of 4 cm (1.56 in)/pixel for DJI native RGB sensor and 6 cm (2.4 in)/pixel for the MicaSense multispectral sensor. Some warping and distortion did occur through the orthomosaic generation process, particularly in areas where there was little overlap on the edges of the acquisition, or where the UAS was likely turning or destabilized from wind. Regions of the orthomosaic which could not be corrected in the processing workflow were clipped out and discarded prior to use in analysis. This resulted in smaller orthomosaics than completed flight areas. See Appendix B for a list of equipment used and general protocol followed for our UAS survey.

2.4. Habitat suitability modeling

Habitat suitability modeling produced predictions of suitable environmental conditions for *H. venusta*. The response variable for all model training and testing was presence-absence species occurrence data. One hundred random points were generated within the core extant population where *H. venusta* subpopulations have been previously documented. These points were assigned as 0 (absent) and 1 (present) based on expert knowledge from recent surveys, identified sub-populations, and outplanting sites (See Figure A.5 showing presence-absence points). Thirty percent of these data were randomly subset for cross-validation evaluation, and the remaining seventy percent were used for model training.

Predictor variables were chosen based on previously characterized ecological drivers for *H. venusta* including slope, aspect, bare soil, and vegetative cover. Variables for the initial satellite-based classification model in the larger AOI included Sentinel-2 satellite surface reflectance imagery (Blue, Green, Red, Near Infrared, Short-Wave Infrared bands, computed Normalized Difference Vegetation Index (NDVI), Normalized Difference Built Index (NDBI), and Bare Soil Index (BSI)), taken from a mean composite of cloud-free images from May through September 2019 in order to best capture leaf-on conditions for the region. Slope and aspect were derived from USGS National Elevation Dataset digital elevation model, and landcover and percent tree cover variables were obtained from the USGS National Land Cover Database. A mean composite from ascending and descending look angles of VV + VH dual-polarization bands was derived from Sentinel-1 C-band synthetic aperture radar (C-SAR) interferometric wide swath (IW) mode (acquired from the same 4-month period in 2019).

Predictor variables for the Core AOI model comparisons included imagery obtained from UAS flights (Blue, Green Red, Near Infrared, and computed NDVI and Visible-band Difference Vegetation Index (VDVI)) and corresponding wavelengths from NAIP and Sentinel-2 imagery from the same extent. Slope and aspect were derived from airborne lidar digital terrain models (acquired from WA DNR Lidar Portal). Table 1 shows all predictor variables used in habitat suitability models and their respective bandwidths, equations, and resolutions where applicable.

Table 1. Environmental predictor variables for habitat suitability models. Large Extent AOI variables were used in the initial GEE classification model, Core AOI variables were used in models for the core population extent.

Model Extent	Variable	Abbreviation	Central Wavelength (Bandwidth) in nm; or equation for Indices	Source	Resolution*
Large Extent AOI	Blue	B	490 (65) / 450 (100) / 475 (20)	Sentinel-2 / NAIP / UAS	10 m / 30.5 cm / 4 cm
Large Extent AOI	Green	G	560 (35) / 550 (100) / 560 (20)	Sentinel-2 / NAIP / UAS	10 m / 30.5 cm / 4 cm

Large Extent AOI	Red	R	665 (30) / 650 (100) / 668 (10)	Sentinel-2 / NAIP / UAS	10 m / 30.5 cm / 4 cm
Large Extent AOI	Normalized Difference Built Index	NDBI	(SWIR – NIR) / (SWIR + NIR)	Sentinel-2	20 m
Large Extent AOI	Bare Soil Index	BSI	((R + SWIR) – (NIR + B)) / ((R + SWIR) + (NIR + B))	Sentinel-2	20 m
Large Extent AOI	IW dual-polarization Synthetic Aperture Radar	VV + VH	5.405 GHz	Sentinel-1	10 m
Large Extent AOI	Landcover class	landcover	NA	USGS National Landcover Database (Landsat-derived)	30 m
Large Extent AOI	Percent Tree Cover	treecover	NA	USGS National Landcover Database (Landsat-derived)	30 m
Large Extent AOI	Elevation	elev	NA	USGS National Elevation Database	10 m
Large Extent AOI	Shortwave Infrared	SWIR	1,610 (90)	Sentinel-2	20 m
Large Extent AOI, Core AOI	Near Infrared	NIR	842 (115) / 850 (100) / 840 (40)	Sentinel-2 / NAIP / UAS	20 m / 30.5 cm / 6 cm
Large Extent AOI, Core AOI	Normalized Difference Vegetation Index	NDVI	(NIR – R) / (NIR + R)	Sentinel-2 / NAIP / UAS	20 m / 30.5 cm / 6 cm
Large Extent AOI, Core AOI	Slope	Slope	NA	USGS National Elevation Database / WA DNR LiDAR	10 m / 0.9 m
Large Extent AOI, Core AOI	Aspect	Aspect	NA	USGS National Elevation Database / WA DNR LiDAR	10 m / 0.9 m
Core AOI	Visible-band Difference Vegetation Index	VDVI	((2 x G) – R – B) / ((2 x G) + R + B)	Sentinel-2 / NAIP / UAS	10 m / 30.5 cm / 4 cm

* Variables were resampled to the same resolution and extent using bilinear interpolation. (10 m for larger AOI, and 0.9 m for the core AOI).

For the larger extent AOI satellite-based model, a Random Forests classification model (Breiman, 2001) was employed due to its demonstrated effectiveness for species distribution and classification in ecology (Cutler et al., 2007). Environmental predictor variables were derived from, and resulting models were run using Google Earth Engine (Gorelick et al., 2017). Model settings were chosen by varying parameters and complexity, and the best performing model was selected (evaluated from metrics derived from an error matrix comparing observed and predicted presence-absence data) that was still ecologically meaningful (Guisan et al., 2017) (pp. 228-230). Appendix C describes settings and choices for all models. The resulting map with classified predictions of potential habitat was evaluated for accuracy based on the subset testing response data; however, its primary function served to provide a baseline of viable sites to target for UAS flights.

To address Objective 2, and the key hypothesis that UAS imagery improves habitat suitability predictions, several models were generated using UAS data and compared to models using data derived from traditional aerial and satellite imagery. UAS model predictions were evaluated against model predictions generated from National Agriculture Imagery Program (NAIP) four-band imagery in 2019 (the most recently available at the time of model generation), and model predictions generated from 2020 Sentinel-2 satellite imagery. All habitat suitability modeling for the core AOI and resulting statistical analyses were performed in R (Computing, 2021) through R Studio (RStudio, 2021).

Following the basic approach described by Guisan et al. (Guisan et al., 2017) (pp. 357-385), and Breiner et al. (Breiner et al., 2018) for model building, four commonly used individual habitat suitability models were generated and two models were ensembled using the biomod2 package (Thuiller et al., 2020). Individual models included generalized linear models (GLM), random forests (RF), Generalized Additive Models (GAM), and Generalized Boosted Models (GBM). These models were chosen due to demonstrated effectiveness for predicting rare species (Breiner et al., 2015; Cutler et al., 2007; Williams et al., 2009). Model parameters and complexity were varied for each individual model (GLM, RF, GAM, GBM), and evaluated using 10-fold cross-validation, and the highest yielding models based on TSS, AUC, and Kappa were kept. Individual models were ensembled using weighted means and committee averaging approaches, because this method has been shown to improve model performance for rare species (Breiner et al., 2018; Marmion et al., 2009). Ensembles were created using a true skill statistic (TSS) as a minimum threshold, calculated from the mean TSS of the top fifty percent of individual models. Appendix C describes settings and thresholding decisions used in model building, and Supplement A links to full example code similar to what was used in this study.

Multicollinearity of environmental variables was addressed though variance inflation factor (VIF) stepwise analysis performed using the usdm package (Naimi et al., 2014), principal component analysis performed using the ade4 package (Thioulouse et al., 2018). Additionally, Pearson's correlation coefficients were calculated using the raster package (Hijmans, 2020). Based on multicollinearity, correlation, and VIF values, NDVI, VDVI, NIR, slope, and aspect were chosen as environmental predictor variables for model comparisons.

Model evaluation was based on an error matrix generated from the performance of the cross-validated 30 percent testing subset of presence-absence response data. Accuracy assessment metrics shown in Table 2, included the true skill statistic (TSS), Accuracy (fraction correct), the Kappa statistic, and the area under the receiver operating characteristic curve

(AUC), which is a measure of the true positive rate against the false positive rate. Additionally, sensitivity and specificity were calculated for a robust evaluation of model performance. Following Allouche et al. (Allouche et al., 2006), we based primary model performance on TSS. After model comparisons were generated, the best performing model was then used to predict habitat for the additional eight UAS survey areas.

Table 2. Evaluation metrics derived from error matrix. TP: true presence, FP: false presence, FA: false absence, TA: true absence, N = TP + FP + FA + TA

Accuracy Assessment Metric	Description	Range	Formula
Accuracy	Fraction of correct predictions	0 to 1	(TP + TA) / N
TSS	True Skill Statistic; Balance of Sensitivity and Specificity	-1 to 1	((TP * TA) - (FP * FA)) / ((TP + FA) * (FP + TA)) = Sensitivity + Specificity -1
Kappa	Sensitive to sample size and prevalence	-1 to 1	((TP + TA) - (((TP + FA) * (TP + FP) + (FP + TA) * (FA + TA)) / N) / (N - (((TP + FA) * (TP + FP) + (FP + TA) * (FA + TA)) / N)
Sensitivity	True Positive Rate	0 to 1	TP / (TP + FA)
Specificity	True Negative Rate	0 to 1	TA / (TA + FP)

Additionally, variable importance and response plots were generated from individual models (see Appendix A.). Variable response graphs plot the probability of occurrence as a function of environmental gradient. These are generated in the biomod2 package through model permutations where all other variables are held at their mean value (Elith et al., 2005; Merow et al., 2014). It is important to note models used in this study are not mechanistic models, therefore variable responses are not directly tied to ecological functions, but still very useful for interpretation.

3. Results

3.1. Satellite-based habitat modeling for UAS mission planning

The binary presence-absence map, generated from the Random Forests (RF) model for the 185 km^2 large AOI, predicted approximately 50 km^2 (19 mi^2) of *H. venusta* habitat. The model performed reasonably well with Sensitivity of 76%, a Specificity of 80%, but the True Skill Statistic of 0.56 indicates the model did not perform much better than random chance. This prediction map still provided a useful baseline for further exploration, and prioritization of UAS and field surveys. Additionally, variable importance derived from the model indicated that Sentinel-1 SAR-derived VV and VH polarization signals, vegetation indices including NDVI, BSI and NDBI, as well as elevation contributed to model predictions. Landcover, slope and aspect contributed the least in variable importance to model prediction results. Table 3 below shows the results of the satellite-based classification model, including variable contribution and model evaluation metrics.

Table 3. Variable importance and model performance of large extent AOI RF model.

Variable	Importance	Model Performance	
Red	28.57	TSS	0.56
BSI	23.12	Overall Accuracy	0.78
VV + VH	23.01	Sensitivity	76 %
NDBI	22.15	Specificity	80 %
Elevation	21.03		
Blue	20.09		
Green	19.65		
NDVI	19.43		
NIR	18.9		
SAVI	15.76		
Slope	15.57		
Aspect	14.21		
Landcover	5.97		

Figure 3 shows the resulting prediction map, with potential habitat in purple. Shaded polygons indicate original areas targeted for UAS flights prior to the field crew going out to perform the surveys. Blue polygons represent revised UAS target flight areas based on limitations of UAS battery life and line of sight restrictions, and the hollow polygons represent a sample of the completed flights. In general, we found we could fly approximately 0.4 Km (0.25 mi) from takeoff based on our UAS setup and terrain conditions. This limitation is acceptable for the purposes of this study, given that future field crews will need reasonable access to get to outplanting sites.

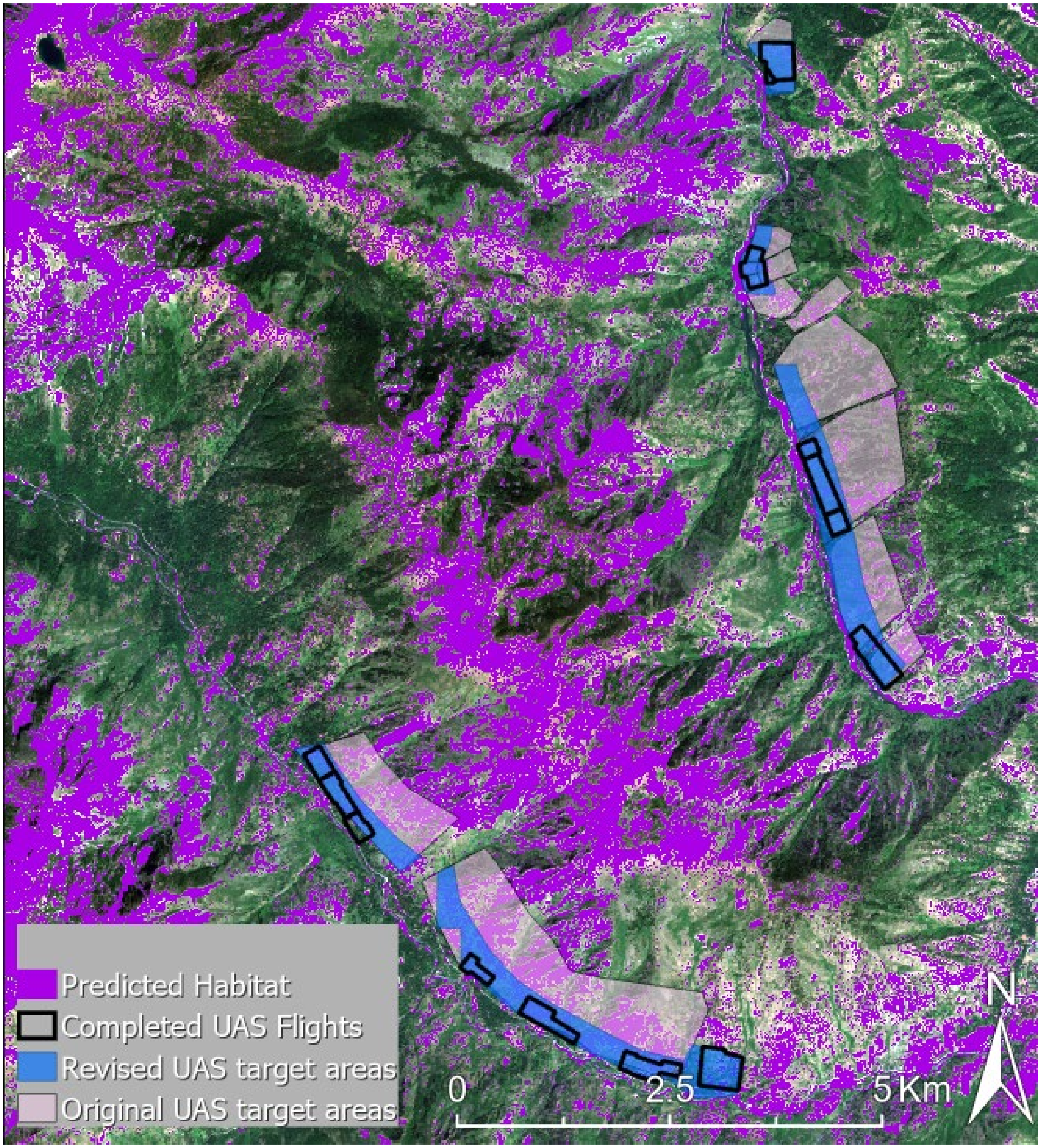


Figure 3. Satellite-based habitat classification prediction map showing potential habitat in purple, with shaded areas originally targeted for UAS flight potential. Blue polygons represent revised target areas for UAS flights based on access to takeoff and landing zones, line of sight, and battery life. Hollow polygons represent a sample of completed flights in the AOI.

3.2. Core AOI HSM comparisons

In general, ensemble models using committee averaging or weighted means outperformed individual models for each sensor type by all accuracy metrics (ensemble models improved by 30% or more in most cases). For individual models, Random Forest and GLM models performed better than GBM and GAM performed worst for all sensor types. Both UAS ensemble models (TSS >0.90) outperformed NAIP (TSS >0.80) and Sentinel-2 (TSS >0.7) imagery, although the NAIP models were nearly equivalent, and resulting prediction maps were very similar visually. Predictions were projected to binary presence/absence maps based on TSS threshold. Fig 4 below shows Sentinel-2 satellite imagery, NAIP aerial imagery, and UAS imagery of the core AOI and the resulting model projections with suitable habitat areas highlighted for visual interpretation. Suitable habitat areas were delineated from previously described subpopulations and outplanting areas, monitoring transects, and inventories (Arnett, 2011).

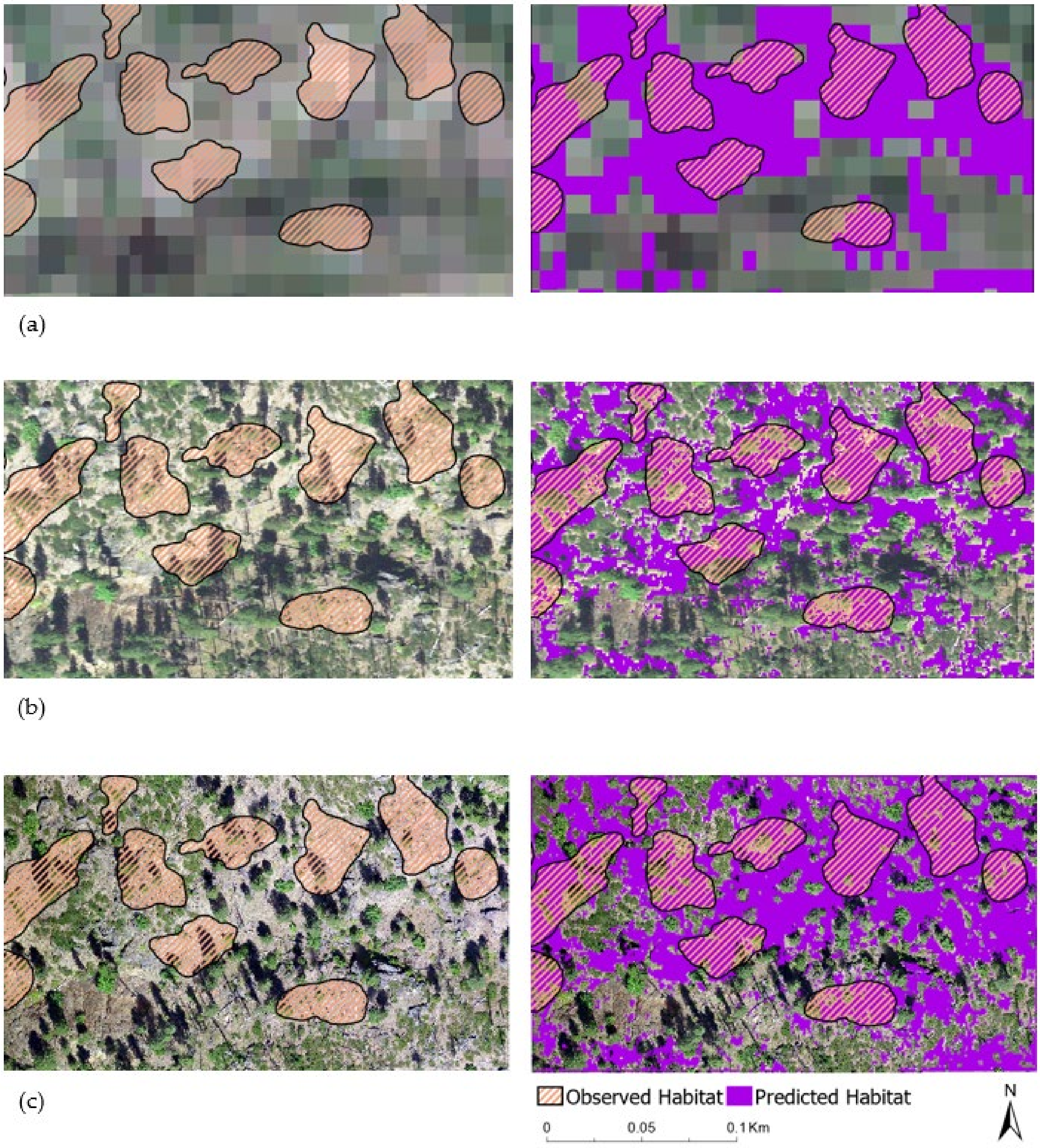


Figure 4. Model results showing 4-hectare core population area of interest predicting suitable habitat overlaid in purple in the right column, and RGB imagery in the left column from: a) Sentinel-2 satellite imagery; b) NAIP aerial imagery; and c) UAS aerial imagery. Hatched polygons

are a representation of suitable habitat for *H. venusta*, based on historic records, inventories, and expert knowledge.

UAS and NAIP models had relatively high percentages for Specificity and Sensitivity (>90%), indicating low errors of commission and omission. Ensemble models had True Skill Statistic (TSS) scores >0.85 for UAS and NAIP imagery. Satellite ensembles also performed reasonably well, with sensitivity and specificity >85%, and ensemble models with TSS scores >0.70. Table 4 below shows all accuracy statistics for individual models and models ensembles by committee averaging (CA) and weighted mean (WM), for each of the three sensor types. The best performing model is the CA ensemble model for UAS imagery with a TSS = 0.91. In all cases, the CA ensemble performed equal to or better than WM ensemble models by accuracy statistic, and nearly all by specificity and sensitivity.

Table 4. Model results for UAS, NAIP, and Sentinel-2. Numbers in bold represent the best performance for each class of model type or accuracy statistic.

	GLM	GBM	RF	GAM	Ensemble (CA)	Ensemble (WM)
UAS						
TSS	0.61	0.65	0.67	**0.50**	**0.91**	**0.90**
ACCURACY	0.81	0.83	0.84	0.75	**0.95**	0.95
AUC	0.80	0.83	0.84	0.75	**0.99**	0.98
KAPPA	0.60	0.64	0.67	0.49	**0.90**	0.90
Specificity (%)	80	85	86	78	93	95
Sensitivity (%)	80	79	81	72	**98**	95
NAIP						
TSS	**0.67**	**0.67**	**0.73**	0.49	0.86	0.82
ACCURACY	0.83	0.85	0.87	0.75	0.93	0.92
AUC	0.83	0.84	0.84	0.75	0.97	0.96

KAPPA	0.66	0.68	0.74	0.48	0.86	0.83
Specificity (%)	81	89	89	69	94	**97**
Sensitivity (%)	85	78	83	75	91	85
Sentinel-2						
TSS	0.59	0.50	0.52	0.55	0.73	0.71
ACCURACY	0.81	0.76	0.77	0.79	0.87	0.87
AUC	0.80	0.73	0.75	0.76	0.92	0.92
KAPPA	0.60	0.50	0.52	0.56	0.72	0.72
Specificity (%)	87	81	80	85	86	92
Sensitivity (%)	70	69	72	70	89	79

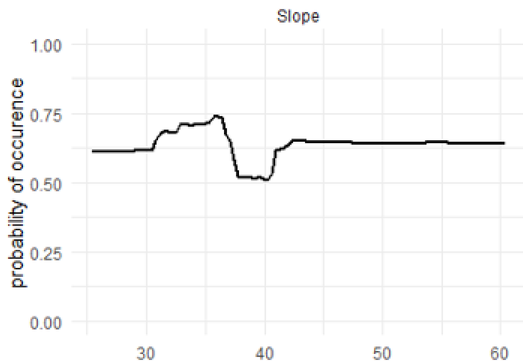
Variable importance for individual and ensemble models indicates that NDVI and aspect were the most important variables for nearly all sensor types and models, with NDVI being the most important driver for prediction of occurrence. Slope was least important for all models, which is likely due to the low variability in slope over the smaller study area. Table 5 below shows variable importance for each individual model and sensor type.

Table 5. Variable importance for each model and sensor type. Numbers in bold represent top two most important variables per model and sensor type. Note that totals will add up to more than 1 because importance is determined based on model permutation with other variables fixed at their mean value.

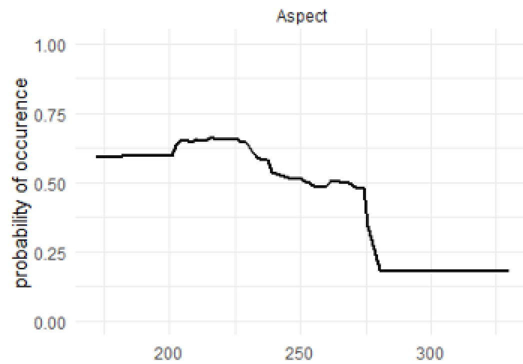
	GLM	GBM	RF	GAM	Model Average
UAS					
slope	0.02	0.02	0.02	0.09	0.04
aspect	**0.27**	**0.15**	**0.15**	0.25	0.21
NIR	0.17	0.05	0.06	0.30	0.15
VDVI	0.26	0.12	0.15	**0.47**	**0.25**
NDVI	**0.45**	**0.35**	**0.34**	**0.56**	**0.43**
NAIP					

NIR	0.02	0.02	0.02	0.20	0.07
NDVI	**0.91**	**0.90**	**0.67**	**0.81**	**0.82**
VDVI	0.15	0.04	0.03	0.22	0.11
slope	0.00	0.06	0.05	0.23	0.09
aspect	**0.25**	**0.11**	**0.13**	**0.38**	**0.22**
<u>Satellite</u>					
NIR	**0.15**	0.08	0.09	**0.26**	0.14
NDVI	**0.77**	**0.52**	**0.36**	**0.60**	**0.56**
slope	0.00	0.01	0.03	0.12	0.04
aspect	0.12	**0.12**	**0.14**	0.22	**0.15**
VDVI	0.00	0.04	0.07	0.11	0.05

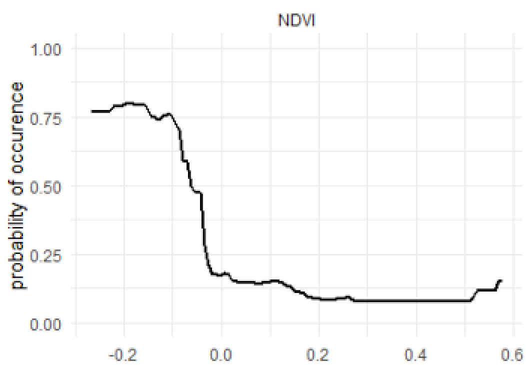
Predictor variable response plots generated for each variable shows predicted presence as a response of environmental gradients. For all models except GAM, probability of occurrence was high for lower NDVI values (< 0.0) and decreased with increasing NDVI values. Probability of occurrence was higher for VDVI values of 0.03 to 0.1, aspects of 200 to 270 degrees, and generally positively correlated with increasing NIR values. GLM response plots held slope at a constant value, and other models had decreasing probability of presence with slopes less than 35 degrees. Figure 5 below shows an example of response plots for predictor variables for a Random Forests model, representing a rough average response for environmental gradients (See Appendix A. for all model response plots).



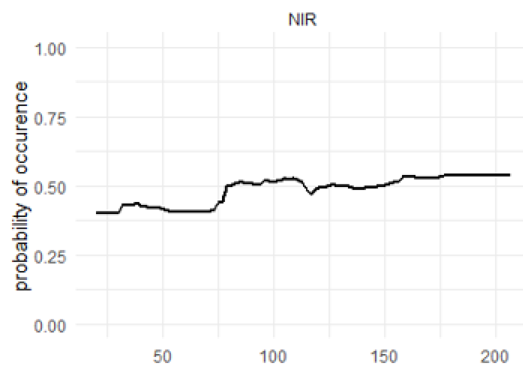
(a)



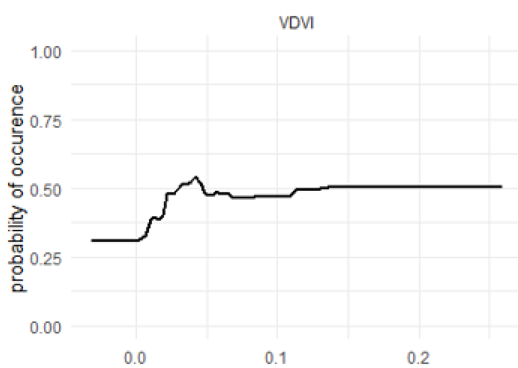
(b)



(c)



(d)



(e)

Figure 5. Response plots for an individual Random Forests model. The black line indicates probability of presence as a function of variable gradients when all other variables are held at their mean. Plots show: a) Slope in degrees; b) Aspect in degrees; c) Normalized Difference Vegetation

Index (-1 to 1); d) Near Infrared reflectance (0 to 255); e) Visible-band Difference Vegetation Index (-1 to 1)

Bivariate response plots were also generated from individual models, which plot the probability of occurrence against two predictor variables in 3-dimensional space. This is useful for examining potential interaction effects between two variables. Figure 6 below shows an example of a bivariate response plots, indicating regions of suitable habitat between two variable gradients.

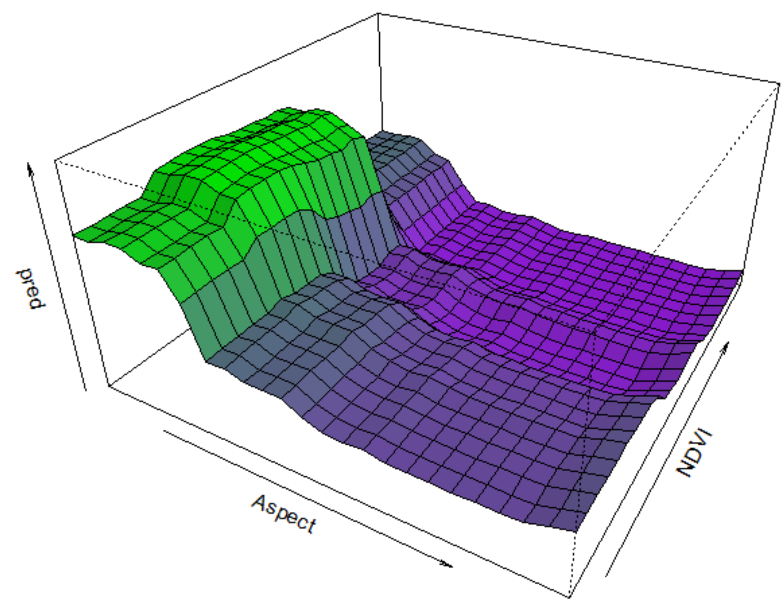


Figure 6. Example of a bivariate response plot showing probability of occurrence on the Z-axis, Aspect and NDVI on the Y- and X- axes. This is a useful way to visualize the effect of two predictors on prediction models in three-dimensional space.

The best performing CA Ensemble Model from UAS imagery was applied to the eight UAS flight areas prioritized from satellite modelling efforts, resulting in projection of approximately 52 hectares (128 acres) of suitable habitat for future field monitoring efforts.

These sites represent the potential habitat for future outplanting of greenhouse-grown *H. venusta* seedlings and will be prioritized for field visits. This result effectively narrowed the 50 km^2 predicted areas from the coarse-scale large aoi satellite model to 52 hectares for recovery team field visits, prioritizing locations for land managers. Figure 7 below shows an example of predicted suitable habitat in one of the areas where the best model was projected. Unfortunately, a quick visual analysis reveals that large boulders and rock outcrops were not well separated from bare ground, and do not represent suitable habitat for *H. venusta*, demonstrating a major limitation for the model to project to adjacent regions. Future iterations of model refinement will need to separate areas of bare ground from exposed rock and boulders.

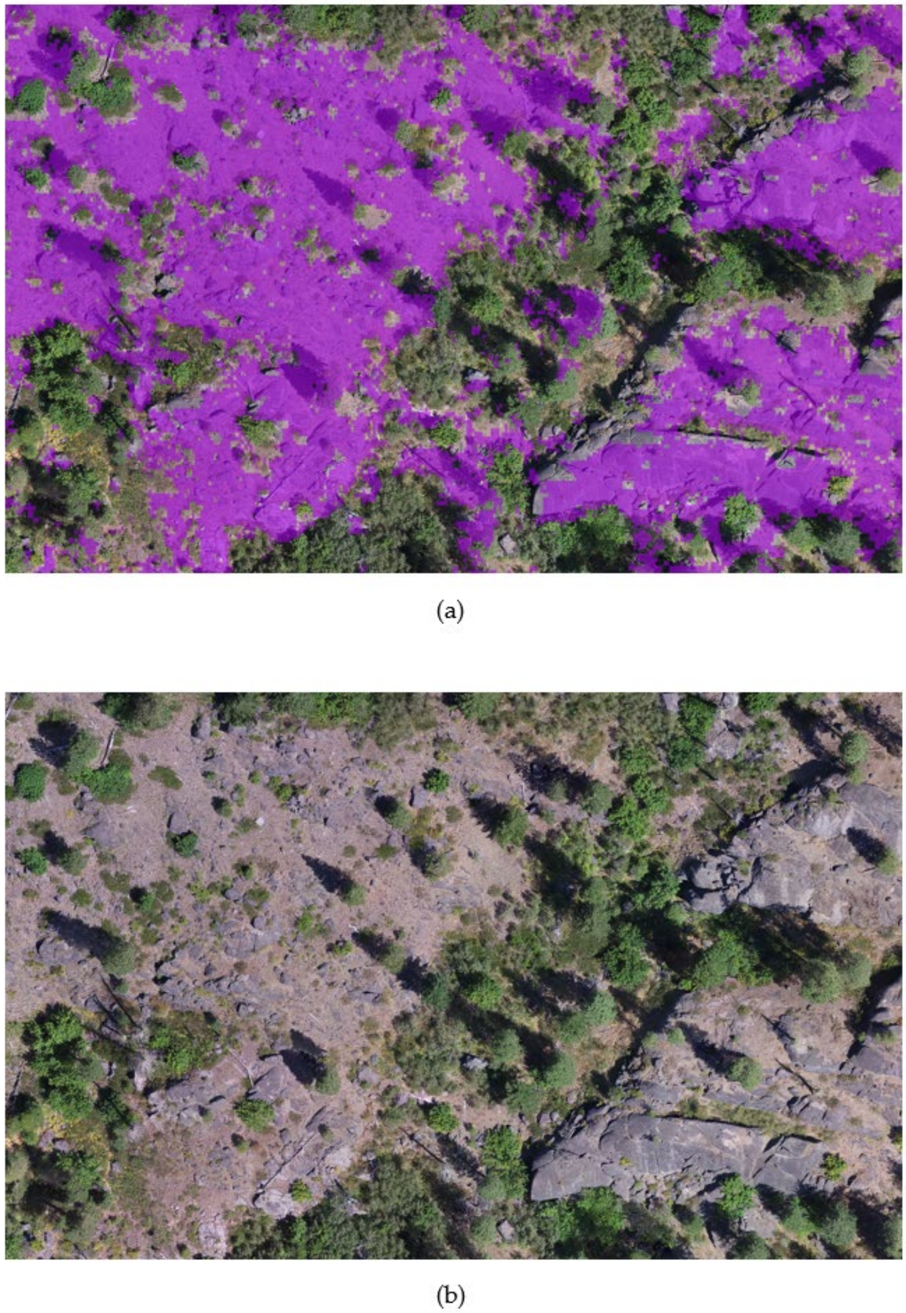


Figure 7. A sample area where the best performing ensemble model was projected: a) Purple colored region represents predicted habitat; b) UAS imagery of the same area. Large boulders and rocks were classified as potential habitat, which misrepresents suitable area for plantings.

4. Discussion

This study aimed to assess the utility of UAS data in plant conservation through a case study of a rare endemic plant, predicting suitable habitat for *Hackelia venusta*. Through this effort, we found that UAS can be applied as an effective tool to acquire high spatial resolution imagery for targeted recovery efforts of a rare species. Overall, model comparisons demonstrate that UAS imagery performed well in predicting suitable habitat for a rare herbaceous plant species, comparable to aerial imagery, and much better than the highest resolution publicly available satellite imagery. The main advantages of UAS we identified in our study include increased spatial resolution of multispectral imagery and spatially targeted temporal discretion for where and when to acquire imagery. This allows for researchers and resource managers to have greater flexibility and options to rapidly acquire targeted, repeatable, and affordable remote sensing data, facilitating decision-making and data driven conservation efforts.

Our initial approach to model potential habitat using 10 m spatial resolution satellite imagery allowed us to effectively identify and prioritize target areas to perform UAS survey flights, reducing total field visits, and refining model variable selection. The workflow followed in this study is not particularly novel, but valuable for prioritizing limited time and resources spent in the field. Following this method supports an adaptive management approach toward species recovery efforts and actions. Field validation of areas predicted from UAS data and habitat suitability models, in addition to seedling establishment success from outplanting efforts in predicted habitat, can inform future iterations of modeling and identifying suitable habitat, focusing management actions and policy direction as new information is collected. This approach allows for additional model inputs, changing environmental conditions and policy direction, and can easily be applied to other species of interest. Furthermore, targeted UAS acquisitions can be used by land managers and field personnel for decision making, quick visual and in-depth modeling analysis.

These targeted UAS acquisitions come at a fraction of the potential cost of similar high-resolution imagery (Sankey et al., 2018). And while it is difficult to directly compare costs between UAS, aerial, and satellite borne products, several studies have shown UAS represent a cost-effective tool for collecting a variety of remotely sensed data, particularly when the study area is <20 ha (Jeziorska, 2019; Manfreda et al., 2018; Matese et al., 2015). Following initial investment of the Unoccupied Aerial Vehicle (UAV) and associated sensors, land managers, conservationists, and practitioners can improve their return on investment through leveraging UAS' high return intervals for existing and new acquisitions. For example, we used a DJI Inspire 1 UAV in our study, a model originally released in 2014, and remains a good investment over five years later, perfectly capable of handling a variety of lightweight sensors (<0.5 kg combined).

The primary limiting factors we discovered using our UAS combination involved capturing larger spatial extents. Flight times were limited by battery life, and the steep topography in the study area quickly drained batteries due to climbing in elevation. Limited takeoff and landing zones coupled with tall trees and mountainous terrain made it difficult to maintain visual line of sight, required by U.S. regulations. These combined factors limited the ability to capture the full extent originally predicted by initial satellite efforts. A different UAS setup with larger payload and battery capacity could help to acquire larger spatial extents.

While this study used an RGB camera and multispectral sensor to capture near infrared reflectance, future applications in environmental monitoring will likely include equipping lidar, hyperspectral, or other sensors to UAS to capture more robust structural and physiological data (Sankey et al., 2018; Tmušić et al., 2020), which may be particularly useful in exploring and modeling ecological drivers and species richness (Hakkenberg et al., 2018; Herniman et al., 2020; Kamoske et al., 2021). High density point clouds derived from UAS-lidar may reveal nuances in microtopography, and overcome limitations of photogrammetrically-derived 3D models and orthomosaics, where shadows can obscure differences between vegetation canopy and terrain (Lopatin et al., 2019).

We found shadows to be nearly unavoidable in our study site at northern latitudes with steep terrain, and overcast days were unpredictable for gathering consistent imagery over multiple sites. There are several methods to reduce effects of shadows and improve classification tasks (Liu & Yamazaki, 2012; Lopatin et al., 2019; Singh et al., 2012), however we found that using vegetation indices, such as NDVI and VDVI, instead of RGB imagery, resulted in general success to reduce effects of shadows on habitat suitability predictions. This was an unexpected result of model selection trials and could be an area of future research.

Within the core known population area for *H. venusta*, our habitat suitability models (HSM) performed relatively well with low errors of omission and commission. While UAS models performed marginally better than NAIP, they were effectively similar for the purposes of predicting potential habitat in which to explore future outplantings. Most likely, this is because both sources of imagery were resampled and scaled up to match the resolution of topographic variables used in all models. This result demonstrates UAS imagery as a viable source of multispectral imagery to be used in place of traditional aerial imagery for a wide variety of applications. While recent NAIP imagery was available for our study area, UAS remote sensing data can provide an adequate alternative to areas where there are gaps in temporal resolution, revisit period, or spatial extent.

Model projections to the eight additional UAS survey areas demonstrate poor ability to distinguish rocks and boulders from other bare ground (see example in Figure 7.). This demonstrates a limitation of projecting models to different regions. This issue could be addressed through a simple visual analysis or during field visits to potential reintroduction sites, where recovery team members have discretion on site to rule out what appears to be unsuitable. Alternatively, subsequent models may utilize object-based image analysis (OBIA) to classify boulders and other bare ground classes to determine optimal plant reintroduction sites.

Visual analysis of model results reveals UAS and NAIP HSMs to be nearly identical, where UAS models perform slightly better when evaluated through accuracy assessment metrics derived through an error matrix. As Lu and Weng note, "the error matrix is only suitable for 'hard' classification, assuming the map categories are mutually exclusive and exhaustive and that each location belongs to a single category."(Lu & Weng, 2007) Here we recognize that the error matrix evaluation method, while widely used (Foody, 2002), has limitations for ecological interpretation, and provides a rough rubric for comparing models. In the case of habitat suitability modeling, both aerial and satellite imagery may be perfectly suitable for a species of interest, and preferable over UAS data for species with large ranges and spatial extents. High resolution UAS imagery offers additional benefits such as high return periods, and detailed visual reference for land managers, at the cost of smaller spatial extents. Moreover, UAS can provide spatially targeted data for areas where aerial imagery, or lidar coverage does not exist, or may be outdated following a land cover change event such as fire, landslide, or land clearing.

In early stages of HSM exploration and model selection in this study, we employed a variety of individual models commonly applied in the literature (Breiner et al., 2018; Norberg et al., 2019) (e.g., Random Forests, GLM, GAM, MARS). We did explore using the Maxent algorithm (Phillips et al., 2006), which is widely used for rare species that are narrowly endemic or have small sample sizes (Abdelaal et al., 2019; Elith & Leathwick, 2009). However, Maxent is typically chosen as a solution for presence-only datasets, and not generally used when presence-absence data is available (Hao et al., 2019). Using the Maxent model would have required using a presence-only subset of our response data, so we chose to leave it out of the set of individual models chosen. Ultimately, our final ensemble modeling approach was effective, outperforming individual models. This outcome validates results of Marmion et al (Marmion et al., 2009), Guisan et al (Guisan et al., 2017) and others (Araújo & New, 2007; Breiner et al., 2015) finding that ensemble models provide more robust predictions than single models.

Ensemble model approaches have demonstrable utility in species and habitat modeling, and as Breiner et al point out, a beneficial future expansion of ensemble models includes visualization of predicted responses to environmental variables for improved ecological inference and understanding (Breiner et al., 2018). While an ensemble model approach may improve classification accuracy, the broader goal in conservation is to better understand the ecological niche a species inhabits, and the role environmental variables play in affecting species distribution. HSMs effectively fit a realized niche for a given species in terms of abiotic environmental conditions (Guisan et al., 2017) (pp. 33-40). We have demonstrated how a realized niche might be modeled for a rare herbaceous plant species using a limited number of readily available remotely sensed environmental variables, based upon an ecological understanding of species habitat requirements (Austin, 2002; Bell & Schlaepfer, 2016).

In choosing fewer environmental predictor variables, we hoped to keep our model simple, which has been shown to avoid over-fitting, facilitate understanding and interpretation of drivers of species occurrence, and remain generalizable to projecting in space and time (Merow et al., 2014; Zurell et al., 2012). This also allows for flexibility in changing model settings and parameters as more ecological insights are revealed through empirical studies. Future modeling endeavors for *H. venusta* may incorporate future scenarios of climate change, dispersal and attrition factors, and biotic interactions to better understand recovery potential.

Understanding ecological drivers is important for model building, prediction, and translating that into management actions (Merow et al., 2014). Variables chosen in this study followed known ecological drivers of *H. venusta*'s habitat, and availability in the studies' extent of interest. While we found slope was not an important variable through model outputs, it is expected to have an ecologically significant role based on previous field work characterizing species requirements. It is likely that our sampling method did not account for the full range of slopes where *H. venusta* is absent, resulting in limited importance. However, response plots indicate some variation of probability of occurrence, indicating a typical range for species presence. When predicting other sites surveyed with UAS, we included it as an important variable for ecologically relevant predictions.

Response plots relating environmental gradients to model predictions are particularly useful for confirming some ecological drivers and evaluating ecological relevance of predictor variables. These plots help ecological interpretation and confirmation of previous habitat studies. For example, the higher likelihood of presence predicted for the low end of the NDVI gradient supports the finding that *H. venusta* is typically found in areas of low vegetative cover and higher bare ground cover (Gibble, 2015). This supports a future effort to explore indices which include a shortwave infrared band such as a bareness index. Additionally, *H. venusta* has previously been described to occur on slopes averaging 30 degrees, and aspects of 238 degrees. This was supported in model response plots, where *H. venusta* was more likely to be present in these ranges, confirming model effectiveness and supporting context for ecological drivers. Results from the original satellite model over the larger study area indicate that VV + VH polarization signals from Sentinel-1 SAR data, as well as BSI, NDVI and NDBI have potential to predict presence for *H. venusta*, supporting future exploration into higher resolution structural and spectral data acquisition for the study area.

Soil texture, moisture, and substrate are suspected to be important drivers for *H. venusta* occurrence, but soils are typically mapped at a very coarse and inconsistent scale making it a challenging variable to incorporate into modeling efforts. This represents an ecologically important variable not readily available in a remote sensing workflow, and would require more extensive field-based monitoring, ultimately out of the scope of this study. Indirect measures of soil moisture and type may be adequate for modeling efforts. Typically, shortwave infrared (SWIR) or thermal infrared (TIR) reflectance wavelengths are used along with near infrared (NIR) wavelengths to calculate indices such as the Normalized Difference Water Index (NDWI), Bare Soil Index (BSI), or Normalized Multi-band Drought Index (NMDI) (Gao, 1996; Wang & Qu, 2007). SWIR and TIR reflectance may be derived from a UAS-based sensor, as air- and space-borne products may be too coarse resolution relative to the study area in question. These derived indices may provide an indirect, remote sensing based solution to soil characterization, including different classes of bare ground, soil moisture, or possibly presence of grasses and small forbs.

Forecasting shifts in distribution and abundance in response to climate and anthropogenic stressors will be an essential task for future *H. venusta* conservation efforts and maintaining sustainable populations. Many species distribution models (SDMs) and HSMs use coarse-scale (> 1 km) bioclimatic variables to forecast distribution changes under different climate change scenarios (Guisan & Thuiller, 2005). However, a species such as *H. venusta*, which occurs in such a narrow extent, has little variation over its known range for environmental variables such as mean annual rainfall or mean summer temperature for example (or other bioclimatic variables). At the 1-km scale, this species occurs in one or two pixels, presenting an inappropriate match in spatial resolution between bioclimatic predictor variables and species occurrence, and would not meaningfully fit the climate-species relationship. Considering this, forecast modeling becomes a more complex endeavor, and future modeling efforts may need to gather more localized data in the field to incorporate soils information and climate forecasts. Other plant and animal species within potential habitat, which may compete with and affect population dynamics of *H. venusta,* should also be factored into future models.

5. Conclusions

We found that UAS can be a useful tool for plant conservation and ecology, providing high resolution imagery for visual analysis, interpretation, and modeling. UAS may be rapidly deployed for targeted, repeatable flights, and fill gaps in space and time where other data may not be available. In this study, we demonstrated an approach using traditional aerial and satellite data to create a workflow to prioritize and target UAS acquisitions, which can reduce field visits and refine model parameters. UAS are increasingly becoming a standard tool for land managers, researchers, and biologists, facilitating rapid data acquisition and revisit periods to aid in adaptive management and decision making. The application of UAS imagery in habitat suitability models remains largely unstudied and warrants further exploration for applications in plant conservation, ecology, and environmental monitoring.

Our study successfully identified potential habitat for future *H. venusta* outplantings and helped substantiate ecological drivers for its habitat requirements. We found that UAS data performed comparably well to conventional aerial imagery and outperformed publicly available satellite data. Important next steps include regular monitoring of *H. venusta* population numbers without negatively impacting its fragile habitat. Low altitude UAS flights and improved spatial resolution may help to aid in a remote sensing approach to monitor plant demographic trends including individual plant detection and regular census. *H. venusta* presents a particularly challenging species for a remote sensing approach, in that it often grows at the base of trees and boulders, often obscured in imagery. UAS-based lidar could be a useful tool to explore these gaps in optical imagery, and aid in higher resolution topographic variables. Additionally, understanding how future climate change will affect potential habitat and species abundance will be critical in managing this endangered species. UAS may not be able to address all these complex issues, but it is certainly a useful tool for species conservation.

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Chapter 3. General conclusions and future research

This Master's Thesis project was a small part of a larger ongoing effort to recover the population of a rare endemic plant, exploring an application of UAS as a tool toward conservation. While initial attempts to identify individual plants were unsuccessful, important goals were met to identify potential sites for *Hackelia venusta* outplanting populations. The process yielded a remote sensing-based workflow to model and predict species habitat which can be applied to a wide variety of applications in conservation and ecology (e.g., monitoring wildlife, wetlands, hydrology, invasive species, geomorphology, and more). We were also able to demonstrate an applied example of habitat suitability model comparison using UAS data alongside conventional forms of remote sensing data (e.g., space- and air-borne data).

In addition, nearly 150 hectares of very high resolution (<10 cm/pixel) multispectral imagery was generated for stakeholder use and analysis. Multispectral imagery is useful for vegetation monitoring and mapping through calculated indices such as the normalized difference vegetation index (NDVI) and NDVI using the red edge band (707-727 nm). Future remote sensing variables for model building should be prioritized based on *H. venusta*'s niche requirements, including thermal data to estimate temperature and soil moisture indices, leaf area index (LAI) to estimate productivity, geomorphic and vegetation structure from laser scanning or photogrammetry, and disturbances from time series analyses (Leitão & Santos, 2019). We developed a repeatable adaptive workflow for recovery team members to fly the same surveys on a regular basis, yielding a high spatial resolution time-series dataset used to monitor disturbance, vegetation cover change, and shrub encroachment at the existing core *H. venusta* population or at new outplanting sites (USFWS, 2019). This workflow to prioritize UAS surveys can be used as a template for other efforts to seek out species habitat, identify undiscovered populations, or monitor areas of interest for change over time.

The models produced in this project both reinforce known ecological drivers, as well as establish a path to further explore environmental drivers for predicting *H. venusta* presence, including aspect, bare ground types, and microtopography (<1 m). Additional environmental predictor variables may provide more ecologically meaningful model predictions. Soil texture, depth, and composition has been identified as an important driver for *H. venusta* occurrence but is not readily available appropriate to the scale of species occurrence. Considering this, it may be worthwhile to explore indirect variables which correlate well with soil types, such as a bareness or soil moisture index derived from shortwave infrared and visible reflectance wavelengths (Wang & Chu, 2007). Furthermore, as models are improved through field data collection and verification, modeling efforts can be used to designate critical habitat for future *H. venusta* conservation efforts (Franklin, 2010; Valavanis et al., 2004).

The modeling approach presented in this study is admittedly static with limitations to forecast into future scenarios of climate change. An important area of future research will be developing a model capable of predicting how *H. venusta* populations may change of time, and how resilient they will be in the face of a changing climate and fire regimes, human and other environmental stressors. As Anderson et al. (2021) point out, ecology and conservation has shifted dramatically in the past three decades. Modern computing power and the Markov chain Monte Carlo sampling method has generated a massive growth in the use of Bayesian statistical analysis. Additionally, integrating different types of models provide the ability to combine multiple sources of data, incorporate important biological processes, accommodate differing sampling designs, biases, and uncertainty to improve species distribution modeling (Case & Lawler, 2017; Fletcher et al., 2019). As population census' for *H. venusta* are carried out, it will be important to incorporate demographic trends into modeling efforts, factoring in mortality, dispersal, and competition.

While parameter selection could have been more rigorous during the tuning process (See Appendix C), it is likely the evaluation method based on known versus predicted occurrences would be inflated (Lobo et al., 2007). The focal species in this study occurs in an extremely narrow spatial extent, and there remains much uncertainty about specific environmental conditions under which this species may thrive. The typical approach toward HSMs and SDMs is to extrapolate environmental conditions where a species exists to new areas, without knowing the full range of potential habitat conditions where a species could thrive. As further information is elucidated through laboratory and greenhouse testing, model parameters may be adjusted accordingly to determine a more appropriate model (Hirzel & Le Lay, 2008). Using the sparse species occurrence data available for *H. venusta*, typical for a narrow endemic species, we generated a predictive model that performed well enough to identify potentially suitable locations. These locations will be scouted in person for final site selection for outplanting reintroduction sites. Ultimately, seedling success in future outplanting sites will be the true model evaluation test.

With the rapid growth of UAS applications in conservation and ecology (Simic Milas et al., 2018), they are already becoming an established monitoring tool regularly used by practitioners in the field. An obvious next direction for this project will be attempting a remote sensing approach to identify and monitor individual *H. venusta* plants (Tay et al., 2018). This might be achieved through low-altitude (< 50 m AGL) sub canopy UAS flights (Rominger & Meyer, 2019), or an alternative method to achieve <1 cm/pixel spatial resolution such as attaching a different type of optical sensor. UAS-borne lidar may also be a worthwhile next step for exploring microtopography or fusing with multispectral data to resolve individual plants (Sankey et al., 2018). Hyperspectral sensors have been shown to aid in remotely based species identification (Alonzo et al., 2014; Fassnacht et al., 2016), but initial field results with a handheld spectrometer did not yield obvious differences in spectral signatures between *H. venusta* and similar herbaceous forbs in its habitat.

Further exploration of multi-spectral and hyper-spectral imagery may be worthwhile. For example, we used a multispectral passive optical sensor on our UAS setup, but new areas of research are being explored for other types of passive and active sensors. UAS-borne lidar, thermal infrared, and hyperspectral sensors have proven applications in monitoring invasive plant species (Papp et al., 2021), vegetation mapping (Prošek & Šímová, 2019), forestry and agriculture (Adão et al., 2017; Pádua et al., 2017). How can they be applied in environmental monitoring and broader species conservation efforts? As Komárek (2020) points out, it is important to assess limitations, data processing capabilities, and costs of remote sensing technology based on the needs of each study. When exploring frontiers in research and applications of new technologies, there may be justifiable costs associated with exploring different sensor types and UAS combinations, but the everyday field practitioner or land manager may be able to answer questions and make decisions with simpler tools at hand.

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Appendix A: Additional figures and tables

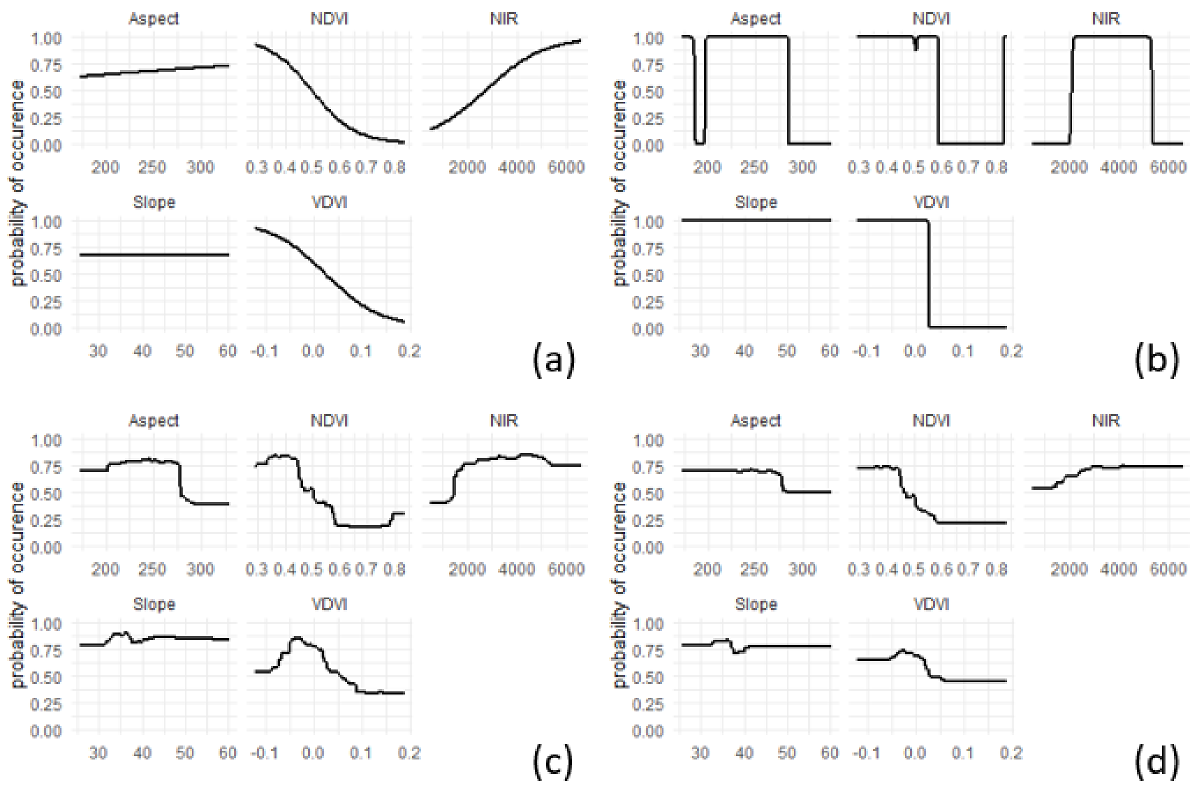


Figure A. 1. UAS-based model response plots for individual models, showing probability of occurrence on the y-axes and environmental gradients on the x-axes, for: a) Generalized Linear Model (GLM); b) Generalized Additive Model (GAM); c) Random Forests (RF); and d) Generalized Boosted Model (GBM).

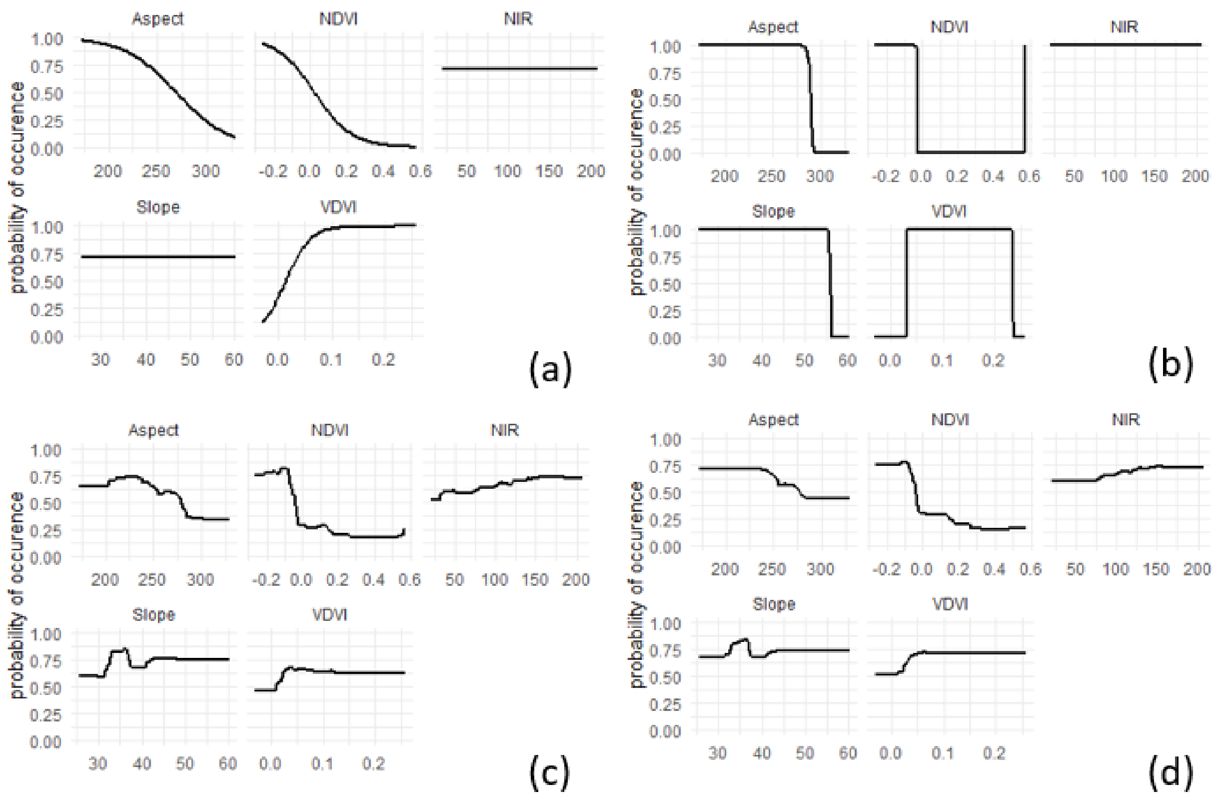


Figure A. 2. NAIP aerial-based model response plots for individual models, showing probability of occurrence on the y-axes and environmental gradients on the x-axes, for: a) Generalized Linear Model (GLM); b) Generalized Additive Model (GAM); c) Random Forests (RF); and d) Generalized Boosted Model (GBM).

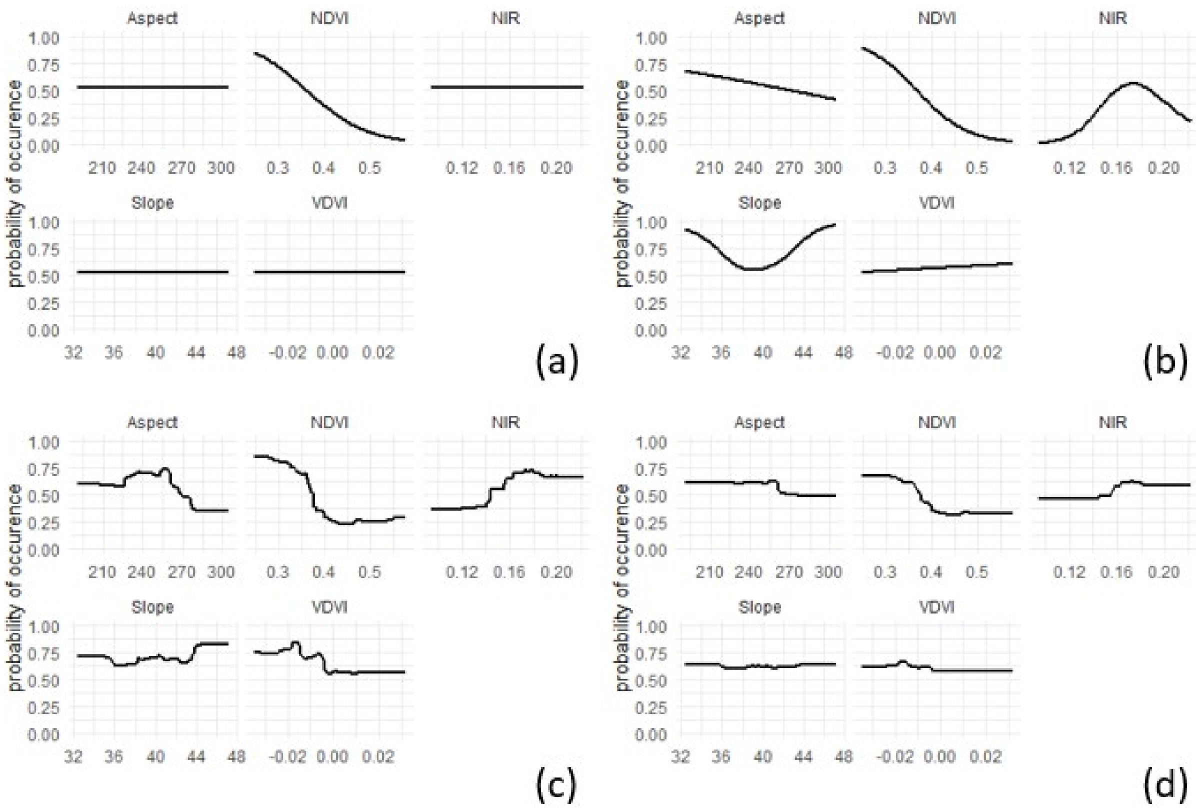
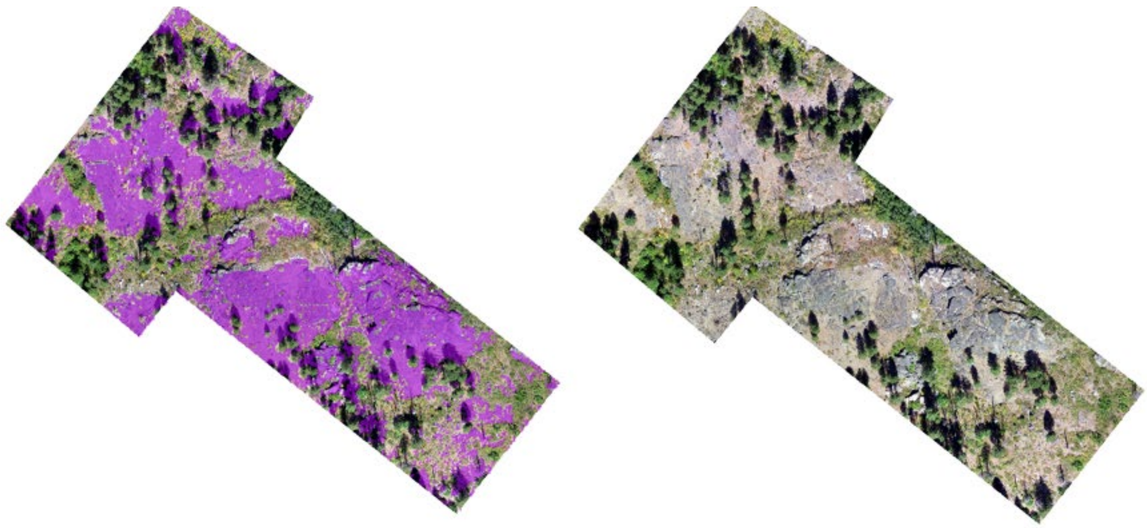
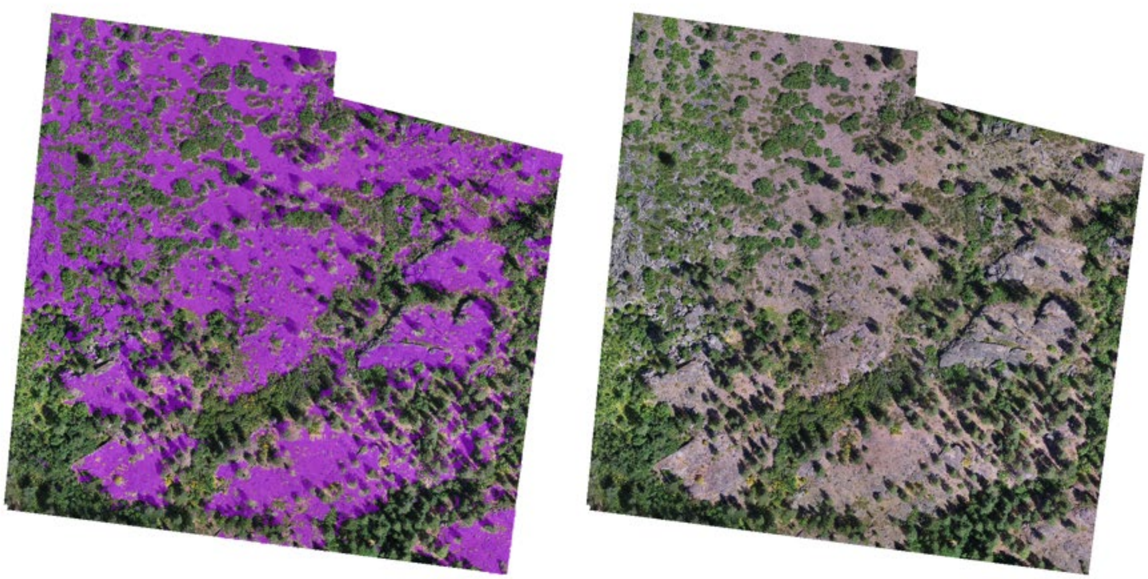


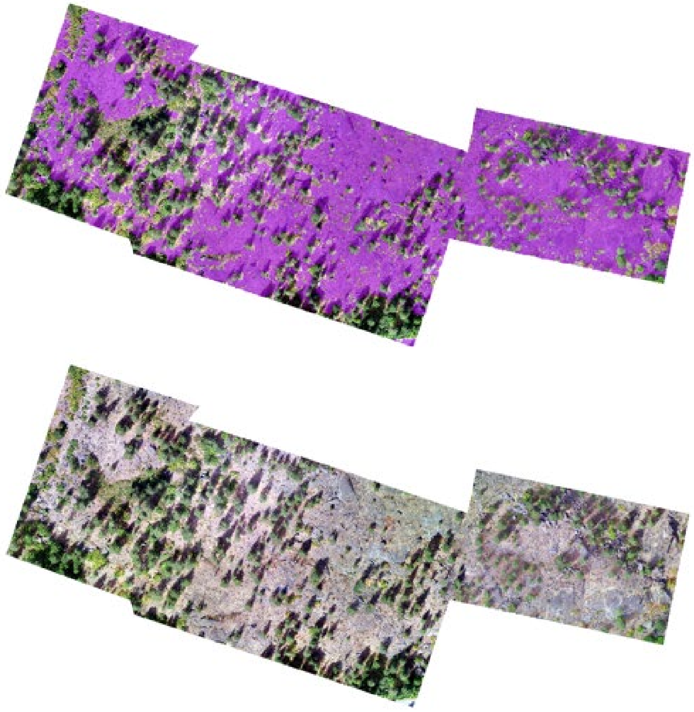
Figure A. 3. Sentinel-2 satellite-based model response plots for individual models, showing probability of occurrence on the y-axes and environmental gradients on the x-axes, for: a) Generalized Linear Model (GLM); b) Generalized Additive Model (GAM); c) Random Forests (RF); and d) Generalized Boosted Model (GBM).



(a)



(b)



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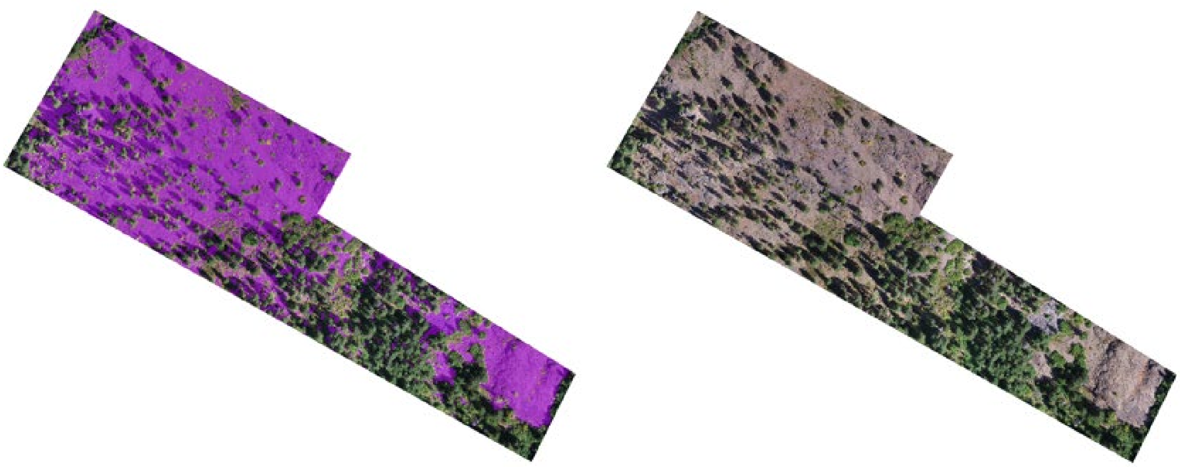

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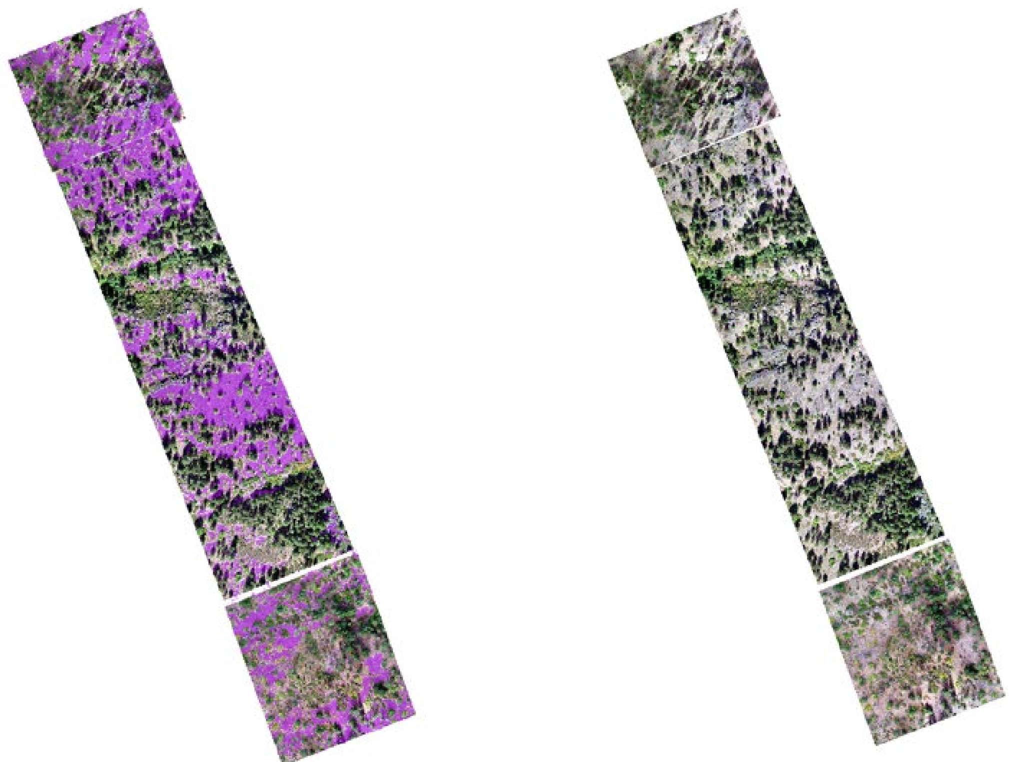

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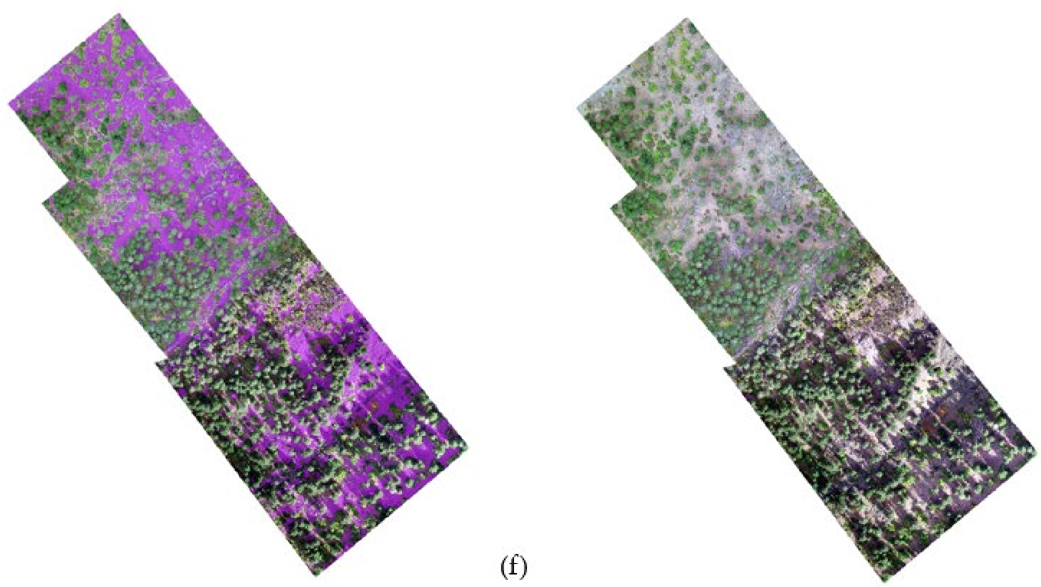

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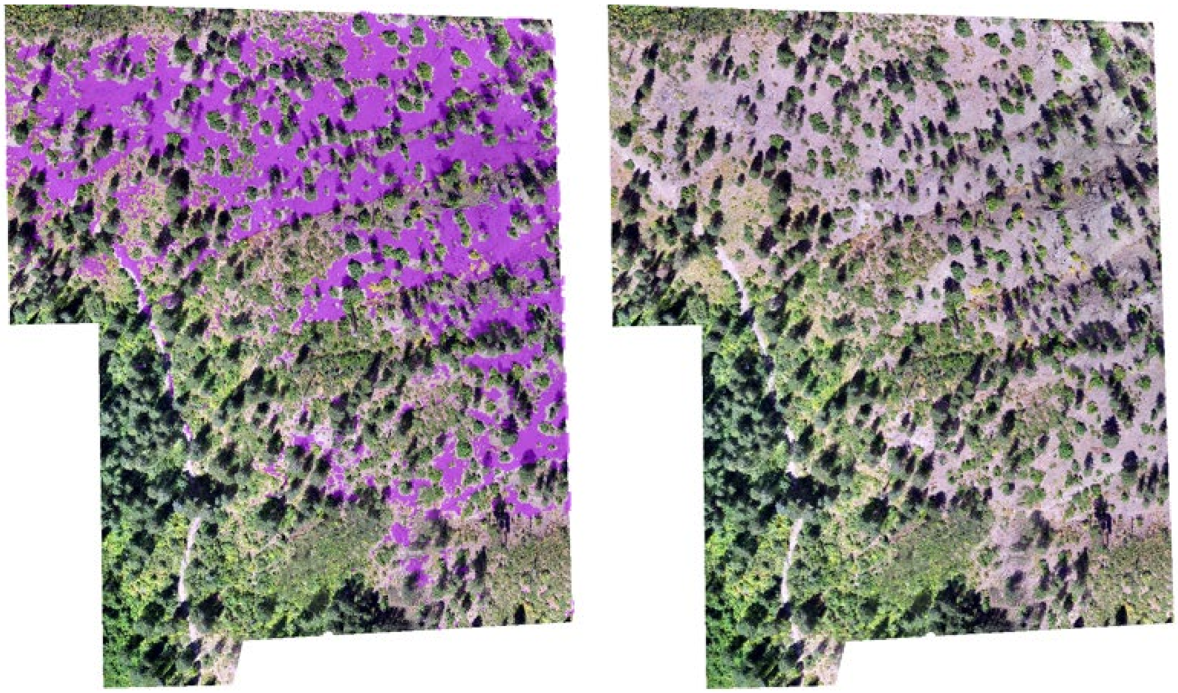
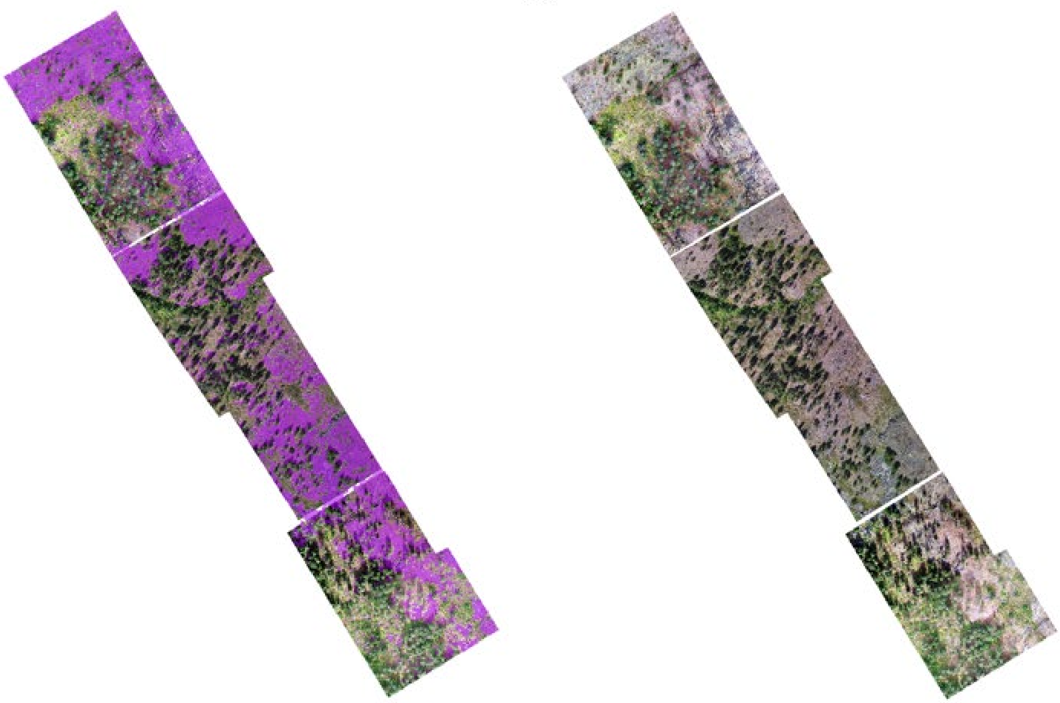


(g)



(h)

Figure A. 4. Images a) – h) show the eight areas where UAS imagery was collected, with predicted potential habitat shown in purple compared to the native RGB imagery.

Figure A. 5. Presence-Absence points generated for the core AOI study area

Appendix B: UAS field protocol

B.1. Introduction

UAS can be an incredibly valuable tool for environmental monitoring and acquiring very high-resolution remote sensing data. Many excellent resources already exist outlining explicit protocols, workflows, and checklists for UAS surveys for environmental monitoring. The following document is not meant to be an exhaustive review, as many resources are readily available for the researcher or hobbyist. This provides the basic workflow and protocol we employed, equipment specifications, and some basic limitations and challenges we faced. Hopefully, this gives the reader a clearer understanding of how we did the UAS surveys described in Chapter 2.

Tmušić et al (2020) provide an excellent practical working overview for UAS data collection in environmental studies. It is worth reviewing the key activities they cover in their review before beginning a study using UAS, which include a study design, pre-flight field work, the flight mission, data processing, and various quality assurance steps. Much of the protocol described here is loosely adapted from their review paper.

B.2. Equipment and software used in this study

UAV: DJI Inspire 1, model T600; weight: 3060 g (including propellers, batteries, and camera); Camera: Zenmuse X3 (12.76 MP, 1/2.3" CMOS, 94° FOV, 20 mm f/2.8 lens); batteries: 2 x DJI TB48 5700 mAh Intelligent Flight Battery; 4 x DJI TB47 4500 mAh Intelligent Flight Battery; Remote Controller: DJI GL658A connected to Samsung Galaxy smartphone; full specs: https://www.dji.com/inspire-1/info.

Multispectral sensor: MicaSense RedEdge 3 [12-bit RAW, 5.5 mm, 1280 x 960 global shutter, 1 capture/sec (set to automatic), 47.2° FOV, 5 bands: center wavelength (bandwidth) in nm: Blue: 475 (20), Green: 560 (20), Red: 668 (10), red edge: 717 (10), near infrared: 840 (40)], weight: 150 g; connected to 3DR GPS and downwelling light sensor (DLS); power source: RAVPower 10000 mAh USB power bank; mounted on 3D locally-printed mount; full specs: https://support.micasense.com/hc/en-us/articles/226364087-RedEdge-3-Integration-Guide.

Flight planning software: UgCS Pro (SPH Engineering, Latvia), photogrammetry tool for UAV Land Survey Missions; installed and run on Apple MacBook Air.

Data Post-processing software: Agisoft Metashape Professional (Agisoft, LLC, St. Petersburg, Russia)

B.3. UAS protocol

***Note**: When conducting UAS surveys for a research institution and within the U.S.A., ensure pilot and UAS are certified and registered in accordance with 14 CFR part 107. More information can be found here: https://www.faa.gov/uas/commercial_operators/.

Study Design: A thorough study design is critical to plan for an appropriate UAS flight mission. UAS survey requirements are linked to the specific research question being addressed, and data type and quality (e.g., platform, sensor configuration, resolution, precision, accuracy, revisit period, etc.) should be determined in advance. Key elements of a study design include: 1) UAS regulations and legislation; 2) platform and sensor choice; 3) camera settings and UAS flight planning software; and 4) georeferencing approach.

Pre-flight mission planning: The study design should drive the steps in pre-flight mission planning. This may include fieldwork such as assessment and reconnaissance of survey area, ground control point distribution, radiometric calibration, and field data collection (e.g., ground truth field measurements, reference, and validation data).

Pre-flight Checklist (adapted from Tmušić et al (2020)):

Check	Action
	Pre-field
	Check weather forecast (Temp, wind speed & direction, relative humidity, pressure, clouds, fonts, visibility); triangulate nearby weather stations if necessary; Check solar noon timing
	Check airspace regulations (temporary flight restrictions (NOTAMS and TFRs in the U.S.A.), acquire necessary permits and waivers and give notice of flight as necessary)
	Make sure all electronics are fully charged (including UAS batteries, R/C, smartphone/tablet, laptop, batteries for additional sensors, etc.)
	Ensure adequate free memory for SD cards and memory storage
	Program flight plan in flight planning software as appropriate (Calculate overlap, flight altitude and speed suitable for ground sampling distance, photogrammetric processing, and other goals related to study design); Plan flight according to terrain, vegetation, and other obstacles, using high-resolution DEMs when available
	Establish Ground Control Points as appropriate
	Check for essential equipment (UAS (controller, camera, batteries, propellors), charger, additional sensors and mounts, tablets, smartphones, USB and data cables, SD card(s), landing pad, backpack, fire extinguisher, electrical tape, zip ties, velcro straps)
	In-field
	Check takeoff/landing zone (sufficient GPS coverage, level and free of overhead obstacles, adequate line of sight, minimum presence of people and/ or animals)
	UAS safety and operational check (no presence of /deformation to propellor or frame; propellors are intact and well-fixed; perform compass calibration; connect R/C to UAS; ensure satellite fix for GPS)
	Follow appropriate set-up and calibration steps for additional sensors (e.g., calibration photo for multispectral sensor)
	Set 'return to home' point, establish contingency plan in case of anomaly or R/C disconnection
	Ensure flight plan is loaded from software to UAS
	Execute small manual flight to ensure all systems working properly
	Check physiological condition of pilot and crew members (IMSAFE: Illness, Medication, Stress, Alcohol, Fatigue, Emotion)

Post-flight processing: Radiometric and geometric post-processing is almost certainly necessary for a research project. However, there may be a case where a recreational, informational, or reconnaissance flight may generate useful photos and videos that do not require post-processing. Currently, there are over a dozen well-established software solutions available for mission planning and post-flight processing (see Tmušić et al (2020), Table 3).

For our study, we used Agisoft Metashape Professional, following the workflow to generate orthomosaics and Digital Elevation Models (DEM): https://www.agisoft.com/support/tutorials/beginner-level/. This is a common workflow that begins with radiometric and geometric calibration and correction, then generates a dense point cloud through photogrammetric processing, on which an orthomosaic and DEM is created. These software solutions typically incorporate a georeferencing step in the workflow, and ground control points can be included in that step. Alternatively, indirect georeferencing can be done in separate programs if there exists adequate data appropriate to the spatiotemporal scale of the UAS survey. For example, we had 30.5 cm resolution aerial imagery acquired within less than one year with no major disturbances (e.g., fire, landslide, development), which was suitable for georeferencing UAS data.

Miscellaneous useful equipment:

- Chair
- Table
- Navigation tools (GPS, compass, clinometer, maps)
- Measurement tools (Hypsometer/rangefinder, dbh tape, transect tape)
- Portable power station (or inverter on vehicle)
- Camera
- Plenty of snacks and water!

B.4. Benefits and limitations

There exists exhaustive reviews and studies on the applications, limitations, comparisons, and benefits of UAS in environmental monitoring and other fields. This is a short list of some things we discovered throughout our study and field mission:

Benefits of UAS

- UAS flights are easily repeatable, offering high revisit periods. Programmed missions can be saved and performed over again through the year or in subsequent years.
- Improved spatiotemporal discretion. The user has a lot of flexibility to choose when and where, and rapidly deploy a UAS mission, with much less lead time and planning than chartering an airplane (Müllerová et al., 2017).
- Very high spatial resolution data. Can quickly acquire < 10 cm/pixel resolution remote sensing data, depending on the sensor and flight altitude.
- Flexibility of sensor choice. Depending on study design, research questions, and available equipment, the UAS user has a wide range of choices of passive and active optical sensors, including visible band cameras, multispectral cameras, thermal cameras, and laser scanners (see Colomina & Molina, 2014; Manfreda et al., 2018).
- Targeted monitoring of land cover change (Anderson & Gaston, 2013).
- Affordable, relative to chartering a plane, or purchasing < 1 m satellite imagery (Müllerová et al., 2017).

UAS limitations

- **Take Off/Landing Zones.** Adequate areas near roads and parking areas may not be readily available for takeoff and landing. A portable system using lighter weight UAS may offer ability to hike reasonable distances from roads and parking areas to a desired location.
- **Visual line of sight.** An otherwise good choice of takeoff/landing zone may be limited by visual line of sight restrictions. Challenges include forest openings where tall trees block view of the sky, being in the bottom of a valley, versus atop a ridge, or a steep canyon terrain where cliffs, boulders, and rock outcroppings may obstruct views. Having two or more people in a flight crew can help to maintain visual line of sight, record field notes, set up hardware, and ensure pilot in command is not distracted.
- **Environment: Wind, Rain**. Forecasts are simply that, a prediction of what weather conditions may be like. Often, surveys will be performed far away from an airport or other advanced meteorologic station, and weather can be dramatically different than a local or regional forecast. Triangulating several weather stations, and surveying winds aloft can help improve predictions in remote areas.
- **Battery life.** Rechargeable batteries lose charge over time, it is worthwhile to mark a date on batteries, and recycle them once they're no longer able to hold a useful charge.

- **GPS signal in steep terrain**. Steep valleys, mountains, canyons, forests, and built-up urban areas can deflect and obscure satellite signal, causing mission failure. We found that satellite coverage often improved simply by getting the UAS to sufficient altitude AGL (approx. 50 m).
- **Obstacles**: trees, steep cyn. Flight altitudes may be limited by obstacles and terrain, affecting final ground sampling distance. A lidar-derived digital surface model (DSM, aka canopy height model) may help in accurately planning a flight mission.
- **Sensors: payload & resolution**. There is a tradeoff between equipping sensors and the payload for a specific UAS. Make sure to do thorough research and testing on the specific UAS combination to ensure flight missions are properly timed and executed based on the total payload and battery life.
- **Negative connotation of "drones"**. When flying in a busy area such as a parking area, trailhead, or roadside, many members of the public may be interested in what you are doing. Having two or more crew members is helpful for public interaction to ensure pilot maintains line of sight and control. Realize some people might not be happy about the use of UAS or bring up privacy concerns. Always be polite, maintain safe flight conditions, and be prepared for a variety of public interaction.
- **Varying regulations**. Legislation and regulations will vary from country to country. Due diligence in pre-flight planning includes knowing all local and temporary flight restrictions.

B.5. Selected bibliography for further reference

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Appendix C. Model Specifications

C.1. Model settings overview and justification

Model settings were chosen following the framework outlined in Guisan et al. (2017) (pp. 358 – 380), and models were tuned based on the methodology outlined in Breiner et al. (2018) to calibrate individual models. Model parameters and complexity were varied for each individual model (GLM, RF, GAM, GBM), and evaluated using 10-fold cross-validation, and the highest yielding models based on TSS, AUC, and Kappa were kept. In many cases, the default settings did not yield a difference in model performance, so they were kept. In several cases, models failed to run entirely so those settings were not chosen. Table 1 below shows the model parameters attempted and final choices in bold, and the following sections show code snippets with model settings. The best performing individual models were then averaged and weighted by their mean to form final ensemble models which were once again evaluated based on TSS, AUC, and Kappa. This same approach was used in Google Earth Engine using a Random Forests model, where the best performing model was used to produce the final map to prioritize UAS flights.

Table C.1. Parameter selection for individual models in biomod2 package

Technique	Parameter choices (bold represents final parameter selected
GLM	Interaction Level (0, **1**) Test (**AIC**, BIC) Model Type (L: linear; **Q**: quadratic; C: cubic)
RF	ntree (100, 500, **1000**, 10000) nodesize(1, 2, 3, 4, **5**, 6, 7, 8, 9, 10)
GAM	algo (GAM_gam, **GAM_mgcv**, BAM_mgcv) select (TRUE, **FALSE**) knots (**NULL**, 1, 5, 10)
GBM	ntrees (100, 500, 1000, **2500**, 5000, 7500, 10000) interaction.depth (1, 2, 3, 4, 5, 6, **7**, 8, 9, 10, 11)

	shrinkage (**0.001**, 0.01, 0.05, 0.1, 0.5)

Code snippets are provided below for model settings, as well as a description about threshold selection. See Supplement A. materials for full examples of code used to run models in Google Earth Engine and R.

C.2. Google Earth Engine Random Forest model settings

The Random Forests classifier used in Google Earth Engine is based on Breiman (2001), see https://developers.google.com/earth-engine/guides/classification for an example.

This is a code snippet that was used in the Thesis with model settings, and explanation of arguments:

```
ee.Classifier.smileRandomForest(100, variablesPerSplit: null,
minLeafPopulation: 1, bagFraction: 0.5, maxNodes: null, seed: 0)
```

Explanation of Arguments:

- **`numberOfTrees`** `(Integer):` The number of decision trees to create.
- **`variablesPerSplit`** `(Integer, default: null):` The number of variables per split. If unspecified, uses the square root of the number of variables.
- **`minLeafPopulation`** `(Integer, default: 1):` Only create nodes whose training set contains at least this many points.
- **`bagFraction`** `(Float, default: 0.5):` The fraction of input to bag per tree.
- **`maxNodes`** `(Integer, default: null):` The maximum number of leaf nodes in each tree. If unspecified, defaults to no limit.
- **`seed`** `(Integer, default: 0):` The randomization seed.

C.3. Model settings within the biomod2 package in R

The biomod2 package in R is an ensemble platform for species distribution modeling, developed by Thuiller et al. (2020). Version 3.4.6 was used at the time of this study, current documentation can be found at: https://cran.r-project.org/web/packages/biomod2/biomod2.pdf. The model settings used in this study are detailed below with an explanation of arguments following.

Individual model settings:

Individual model settings in biomod2 are set up through the BIOMOD_ModelingOptions() function, settings were as follows:

```
BIOMOD_ModelingOptions(
    GLM = list(type = "quadratic", interaction.level = 1),
    GBM = list(n.trees = 2500),
    RF = list(ntree = 1000),
    GAM = list(algo = "GAM_mgcv"))
```

Explanation of Arguments:

`GLM (glm)`

* For complete documentation on generalized linear model functions in R, refer to: https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/glm.

- **`myFormula`** : a typical formula object (see example). If not NULL, type and interaction.level args are switched off. You can choose to either:

    - generate automatically the GLM formula by using the type and interaction.level arguments type (default `'quadratic'`) : formula given to the model (`'simple'`, `'quadratic'` or `'polynomial'`). `interaction.level` (default `0`) : integer corresponding to the interaction level between variables considered. Consider that interactions quickly enlarge the number of effective variables used into the GLM.

    - or construct specific formula

- **`test`** (default `'AIC'`) : Information criteria for the stepwise selection procedure: AIC for Akaike Information Criteria, and BIC for Bayesian Information Criteria (`'AIC'` or `'BIC'`). `'none'` is also a supported value which implies to consider only the full model (no stepwise selection). This can lead to convergence issues and strange results.

- **`family`** (default `binomial(link = 'logit')`) : a description of the error distribution and link function to be used in the model. This can be a character string naming a family function, a family function or the result of a call to a family function. (See family for details of family functions.) . BIOMOD only runs on presence-absence data so far, so binomial family by default.

- **`control`** : a list of parameters for controlling the fitting process. For glm.fit this is passed to glm.control.

GBM (gbm)

* See https://cran.r-project.org/web/packages/gbm/gbm.pdf for complete documentation on generalized boosted regression models in R.

- **distribution** (default 'bernoulli')
- **n.trees** (default 2500)
- **interaction.depth** (default 7)
- **n.minobsinnode** (default 5)
- **shrinkage** (default 0.001)
- **bag.fraction** (default 0.5)
- **train.fraction** (default 1)
- **cv.folds** (default 3)
- **keep.data** (default FALSE)
- **verbose** (default FALSE)
- **perf.method** (default 'cv')
- **n.cores** (default 1)

GAM (gam)

* See https://cran.r-project.org/web/packages/gam/gam.pdf for complete documentation on generalized additive models package in R.

- **algo** : either "GAM_gam" (default), "GAM_mgcv" or "BAM_mgcv" defining the chosen GAM function (see gam, gam resp. bam for more details)

- **myFormula** : a typical formula object (see example). If not NULL, type and interaction.level args are switched off. You can choose to either:

    - generate automatically the GAM formula by using the type and interaction.level arguments type : the smother used to generate the formula. Only "s_smoother" available at time. interaction.level : integer corresponding to the interaction level between variables considered. Consider that interactions quickly enlarge the number of effective variables used into the GAM. Interaction are not considered if you choosed "GAM_gam" algo

    - or construct specific formula

- **k** (default -1 or 4) : a smooth term in a formula argument to gam (see gam s or mgcv s)

- **family** (default binomial(link = 'logit')) : a description of the error distribution and link function to be used in the model. This can be a character string naming a family function, a family function or the result of a call to a family function.

(See family for details of family functions.) . BIOMOD only runs on presence-absence data so far, so binomial family by default.

- **`control`** : see `gam.control` or `gam.control`
- some extra `"GAM_mgcv"` specific options (ignored if `algo = "GAM_gam"`)
  - **`method`** `(default 'GCV.Cp')`
  - **`optimizer`** `(default c('outer','newton'))`
  - **`select`** `(default FALSE)`
  - **`knots`** `(default NULL)`
  - **`ParamPen`** `(default NULL)`

RF (randomForest)

* See https://www.rdocumentation.org/packages/randomForest/versions/4.6-14/topics/randomForest for complete usage of randomForest package in R.

- **`do.classif`** `(default TRUE)` : if TRUE classification random.forest computed else regression random.forest will be done
- **`ntree`** `(default 500)`
- **`mtry`** `(default 'default')`
- **`nodesize`** `(default 5)`
- **`maxnodes`** `(default NULL)`

Ensemble Model Options

Ensemble model settings in biomod2 are set through the BIOMOD_EnsembleModeling() function, settings were as follows:

```
BIOMOD_EnsembleModeling( modeling.output = modeling.output,
                         em.by = 'PA_dataset+repet',
                         eval.metric = 'TSS',
                         eval.metric.quality.threshold = 0.7,
                         models.eval.meth =
    c('KAPPA','TSS','ROC','ACCURACY'),
                         prob.mean = FALSE,
                         prob.cv = TRUE,
                         committee. Averaging = TRUE,
                         prob.mean.weight = TRUE,
                         VarImport = 5 )
```

Explanation of Arguments

- **`modeling.output:`** a "BIOMOD.models.out" returned by BIOMOD_Modeling

- **chosen.models:** a character vector (either 'all' or a sub-selection of model names) that defines the models kept for building the ensemble models (might be useful for removing some non-preferred models)
- **em.by:** Character. Flag defining the way the models will be combined to build the ensemble models. Available values are 'PA_dataset+repet' (default), 'PA_dataset+algo', 'PA_dataset', 'algo' and 'all'
- **eval.metric:** vector of names of evaluation metric used to build ensemble models. It is involved for formal models exclusion if eval.metric.quality.threshold is defined and/or for building ensemble models that are dependent of formal models evaluation scores (e.g. weighted mean and committee averaging). If 'all', the same evaluation metrics than those of modeling.output will be automatically selected
- **eval.metric.quality.threshold:** If not NULL, the minimum scores below which models will be excluded of the ensemble-models building.
- **models.eval.meth:** the evaluation methods used to evaluate ensemble models (see "BIOMOD_Modeling" models.eval.meth section for more detailed informations)
- **prob.mean:** Logical. Estimate the mean probabilities across predictions
- **prob.cv:** Logical. Estimate the coefficient of variation across predictions
- **prob.ci:** Logical . Estimate the confidence interval around the prob.mean
- **prob.ci.alpha:** Numeric. Significance level for estimating the confidence interval. Default = 0.05
- **prob.median:** Logical. Estimate the median of probabilities
- **committee.averaging:** Logical. Estimate the committee averaging across predictions
- **prob.mean.weight:** Logical. Estimate the weighted sum of probabilities
- **prob.mean.weight.decay:** Define the relative importance of the weights. A high value will strongly discriminate the 'good' models from the 'bad' ones (see the details section). If the value of this parameter is set to 'proportional' (default), then the attributed weights are proportional to the evaluation scores given by 'weight.method'(eval.metric)
- **VarImport:** Number of permutation to estimate variable importance

C.4. Threshold selection

Transforming a continuous prediction output to a binary response is a common practice when mapping presence-absence species distribution models (Zurell et al., 2020). Commonly used thresholds to transform the data include sensitivity, specificity, overall accuracy, and the area under the receiver operating characteristic curve (AUC; Liu et al., 2005). In our study, thresholds were determined for both model ensemble approaches and binarization of model predictions. Thresholds can also be used to ensemble a subset of individual models and transform continuous response data from species distribution models (Guisan et al., 2017).We chose the true skill statistic (TSS) for both these thresholds because it presents a balanced view of sensitivity and specificity and accounts for omission and commission errors but is not affected by prevalence such as the kappa statistic (Allouche et al., 2006).

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Supplement A. Example code used for modeling.

Example code for individual and ensemble models used for comparison, evaluation, and projection in this study is provided at: https://github.com/drewinthestew/MSthesis/blob/main/HSM_generic_code.R.

Note that explicit species occurrence and environmental variables are not provided to protect the location of the rare, endangered plant, *Hackelia venusta*. The code is meant to provide an example of how this study went about using the biomod2 and other packages in R to generate habitat suitability models (HSM) and could be used as a template for other HSMs of one or more species of interest. A sample of code is also included in the above script to acquire species occurrence records from the Global Biodiversity Information Facility (GBIF).

Additionally, example code for the large extent area of interest (AOI) used to prioritize UAS surveys can be found in Google Earth Engine (need an account to view):

https://code.earthengine.google.com/5dcb0b2093f25aead5b3ad43f09203c0; or:

https://github.com/drewinthestew/MSthesis/blob/main/GEEjsonHSM_LgAOI.