Quantifying Floral Resource Availability Using Unmanned Aerial Systems and Machine Learning Classifications to Predict Bee Community Structure

Jesse Anjin Tabor
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QUANTIFYING FLORAL RESOURCE AVAILABILITY USING UNMANNED AERIAL SYSTEMS AND MACHINE LEARNING CLASSIFICATIONS TO PREDICT BEE COMMUNITY STRUCTURE

by

Jesse Anjin Tabor

A thesis submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

in

Ecology

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2022
ABSTRACT

Quantifying Floral Resource Availability using Unmanned Aerial Systems and Machine Learning Classifications to Predict Bee Community Structure

by

Jesse Anjin Tabor, Master of Science

Utah State University, 2022

Major Professor: Dr. James P. Pitts
Department: Biology

Bees (Hymenoptera: Anthophila) are important for natural and managed ecosystems (e.g., wilderness areas, agricultural ecosystems, urban parks) because of the critical pollination services they provide for both wild plants and cultivated crops. The available floral resources in an ecosystem are one of the most important factors in supporting bee diversity and abundance. Measuring the relationship between the floral community and bee community may enable apiarists and land managers to make informed decisions in managing wild and domesticated bee species. In the present study UAV surveys with machine learning classification analysis and ground transect surveys were used to characterize the spatial temporal variation of floral resources at three unique study areas. The spatial temporal variation of the associated bee communities were also assessed at each study area. Seven flower species totaling 2,137.96 m² of floral area were classified using UAVs, equaling 0.5% of the overall classified landscape. Based on the dynamic changes of floral area classified in UAV images, it was determined that the period of flowering and changes of flower coverage for different species varied. Average sensitivity and specificity for the flower classes throughout the study were 0.77 and 0.99 respectively suggesting good predictive accuracy. Additionally, 2,100 inflorescences from 22 unique flower species were
recorded using the ground transect surveys and 136 bees from 11 genera were recorded using net surveys. I tested the hypothesis that increased bee diversity and abundance would positively correlate with increased floral diversity and abundance using seven simple linear regression models. I found that the floral resource data collected from ground transect surveys predicts bee diversity, bee richness, and bee abundance. I also found floral abundance data captured by UAVs predicts bee abundance in the study region. Finally, I found UAV floral abundance predicts ground transect floral abundance suggesting a positive relationship between different sampling methods. My results support previous research that suggests a high diversity of resources will support a high diversity of insect consumers, and habitats with abundant flowers have greater possibilities for partitioning of available resources. My results also support UAVs as a feasible and efficient method for characterizing floral resources in non-agricultural settings. Further research should include using UAV imagery to quantify floral resources to predict bee community dynamics on a landscape scale.

(127 pages)
PUBLIC ABSTRACT

Quantifying Floral Resource Availability using Unmanned Aerial Systems and Machine Learning Classifications to Predict Bee Community Structure

Jesse Anjin Tabor

Bees are important for agricultural and non-agricultural ecosystems because they pollinate both wild plants and commercial crops. Flowers provide pollen and nectar resources that bees use to survive and reproduce. Measuring the relationship between the floral community and bee community may help apiarists and land managers to make informed decisions in managing wild and domesticated bee species. Manual methods to describe and count flowering vegetation is costly in time and personnel. Unmanned aerial vehicle (UAV) technology may be an efficient way to describe and count flowering vegetation on a large scale. UAVs with classification analysis and ground transect surveys were used to describe the variation in the flower communities at three field sites in non-agricultural environments. The variation in bee communities were also recorded at the field sites. Seven unique flower species were quantified using UAVs. Using the UAV imagery, it was determined that the period of flowering and changes of flower coverage for different species varied. Twenty-two unique flower species were described and counted using the ground transect surveys and 136 bees from 11 genera were recorded using net surveys. I tested the hypothesis that increased bee diversity and abundance would positively correlate with increased floral diversity and abundance using seven simple linear regression models. I found that the floral resource data collected from ground transect surveys predicts bee diversity, bee richness, and bee abundance. I also found floral abundance data captured by UAVs predicts bee abundance at the field sites. Finally, I found UAV floral abundance predicts ground transect floral abundance suggesting a positive relationship between
different sampling methods. My results support previous research that suggests a high diversity of resources will support a high diversity of insects; and habitats with abundant flowers have greater possibilities for partitioning of available resources. My results also support UAVs as an efficient method for describing and counting floral resources in non-agricultural settings. Further research should include using UAV imagery to count flowers to predict bee communities on a landscape scale.
DEDICATION

I dedicate this thesis to my wonderful Grandma Betty.

Jesse Anjin Tabor
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I would like to thank my wife Alison for her support in my undergraduate and graduate school endeavor. Without her patience and understanding, I would not have been able to persevere through the rigors of research and study.

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Jesse Anjin Tabor
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CHAPTER ONE

Introduction

Bees (Hymenoptera: Anthophila) are essential for natural and managed ecosystems (e.g., wilderness areas, agricultural ecosystems, urban parks) because of the critical pollination services they provide for both wild plants and cultivated crops. Bees forage on flowering plants that produce nectar and pollen. Typically, adult bees feed on nectar while their offspring will feed on a mixture of nectar and pollen. While bees collect nectar and pollen for their nest, they inadvertently transfer pollen from stamen to pistil within the flower, between flowers in a plant, or between flowers of different plants (Wilson & Carril, 2015). This results in the production of seeds and the next generation of flowers. Bees are estimated to contribute 86% of the pollination services for wild plants (Ollerton et al., 2011) and about 33% of the pollination services to agricultural crops (Klein et al., 2007). Over 20,000 bee species have been identified around the world and over 4,000 bee species live in the United States alone (Winfree, 2010; Woodard et al., 2020). Most bees can be separated into two categories of female pollen preferences, either generalists or specialists. Generalist bees visit a wide variety of flower types and species whereas specialist bees limit themselves to only a few plant species (Wilson & Carril, 2015). Most bees are solitary with each female bee building her own nest, laying eggs, and gathering resources to feed her offspring (Wilson & Carril, 2015). Other solitary bees share nest construction and guard duties, or live close together but maintain solitary lifestyles (Wilson & Carril, 2015). Conversely, honey bees and bumble bees are highly social, meaning they live in hives with a queen and the workers divide up the duties necessary to keep the hive thriving. Honey bees and bumble bees make up less than 1% of all bee species (Wilson & Carril, 2015).

The European Honey bee was introduced by colonist to the Americas aboard European ships in the early 17th century (Nielsen et al., 1994). By the late 19th century, the crop yield
benefits from honey bee pollination were recognized and beekeeping for pollination services became an integral part of American agriculture (Rucker & Thurman, 2019). Over time the improving transportation technology created the migratory beekeeping industry. By taking advantage of the different blooming periods, migratory beekeepers are able to profit from pollination services throughout the year.

Today large-scale migration routes are traveled by beekeepers and their bees. The pollination season begins each year in February in the almond groves of California (Burgett et al., 2010; Rucker et al., 2012). It is estimated that 2/3 of the three million managed honey bee colonies in the United States are enlisted to pollinate almonds (Rucker & Thurman, 2019). Following the almond pollination beekeepers rent out their colonies to pollinate tree fruits in Oregon and Washington, followed by soft fruits and seed crops (Rucker & Thurman, 2019). After the pollination season, beekeepers typically search for healthy bee pasture to recover colony stocks and produce honey.

The availability of summer forage is critical in economic value and overwintering success for the commercial honey bee keeper. The floral resources in the environment (i.e. pollen and nectar) are needed to support honey production and the reproduction and health of honey bees. Floral diversity and abundance are positively correlated with improved brood rearing, adult longevity, colony growth, colony production, and more successful overwintering of colonies (Döke et al., 2015; Donkersley et al., 2014; Horn et al., 2016; Sponsler & Johnson, 2015; Vaudo et al., 2015). Lack of floral resources can lead to suboptimal bee nutrition resulting in a compromised bee immune system, reduced reproductive success, and poor colony health. These nutrition deficits also exacerbate the negative impacts of parasites and pathogens (Dolezal et al., 2016; Goulson et al., 2015). Additionally, pesticides, invasive species, and climate impacts via drought and elevated temperatures cause added stress to honey bees (Dicks et al., 2021; Hanberry et al., 2020). Beekeepers must avoid contaminated floral resources and gain access to non-toxic
forage sites to reduce harmful exposure to honey bees (Durant, 2019). Consequently, floral resource availability around apiaries are an important consideration when the commercial honey bee keeper determines apiary locations.

Recently, several studies have documented widespread declines in wild and managed bee populations (Hallmann et al., 2017; Seibold et al., 2019; van Klink et al., 2020; Woodard et al., 2020). Development, agricultural intensification, and urbanization have caused a reduction in habitat (i.e. floral resources and nesting space) subsequently leading to inadequate nutrition available for bees (Cane & Tepedino, 2001; Hanberry et al., 2020; Otto et al., 2016; Wojcik et al., 2018). Land use changes from grasslands to monoculture-based farming have reduced the available floral resources (Durant, 2019; Goulson et al., 2015; Otto et al., 2016). Furthermore, reduced enrollment in the Conservation Reserve Program (CRP) and other USDA conservation programs, have reduced healthy forage opportunities and pushed honey bee keepers to seek alternative forage (Doidge et al., 2020; Durant, 2019; St. Clair et al., 2020).

When there is a lack of sufficient floral resources in the environment, beekeepers can supplement with sugar syrup and pollen substitutes to sustain their colonies. However, research found that bees provided with natural forage instead of protein supplements were less likely to be infected with pathogens and parasites, and were healthier (DeGrandi-Hoffman et al., 2016). Protein supplements do not appear to remedy problems of poor nutrition or reduce colony losses and beekeepers prefer to provide bees with a natural source of pollen and nectar (DeGrandi-Hoffman et al., 2016; Durant, 2019). The lack of floral resources has created a need to find additional bee pastures for the commercial honey bee keeper.

As suitable bee pasture becomes more uncommon, beekeepers are increasingly pasturing their hives in natural landscapes on U.S. public lands managed by U.S. Department of Agriculture Forest Service, U.S. Fish and Wildlife Service, and Bureau of Land Management, in search for good bee pasture (Wojcik et al., 2018). However, as a non-native species to North America, there
are unanswered questions about how the introduction of honey bees into these areas may affect native bee species, and vice-versa (Henry & Rodet, 2018). Recent declines in native bee populations fuel concerns that pasturing managed honey bees in natural areas may limit resources for native bees. One study suggested that one average-size honey bee hive extracts enough pollen in one month to support the development of 33,000 native bees (Cane & Tepedino, 2017). Another study estimated a hive of 10,000 workers requires 80 acres of forage (Smart et al., 2016).

Past experiments to examine interactions of multiple species have been performed under a variety of conditions. Studies indicate that honey bees compete for forage with native bees, particularly in times of drought (Cane & Tepedino, 2017; Paini, 2004; D. Thomson, 2004; D. M. Thomson, 2016; Wojcik et al., 2018). Research suggests honey bees reduce food availability, native bee floral visitation rates, fecundity, diversity and nectar foraging success (Henry & Rodet, 2018; Russo, 2016; Torné-Noguera et al., 2016). However, the regional scope of these bee interaction studies are limited because most studies are performed close to production agriculture, and not in the natural landscapes where competitive interactions between managed and wild bees are occurring (Wojcik et al., 2018).

Commercial apiaries may also threaten native bee populations with disease, which can be vectored by flowers (Goulson et al., 2015). During the pollination season, honey bees are exposed to many parasites and pathogens before they are moved into summer production areas, including public lands (Durant, 2019). While foraging on public lands honey bees may come into contact with other native pollinators on shared flowers and disease may be passed between species (Graystock et al., 2015). Studies have demonstrated virus transfers from honey bees to several other genera including *Andrena*, *Ceratina*, *Bombus*, *Osmia* and *Xylocopa* (Tehel et al., 2016).

Beekeepers are dependent on environmental conditions that drive many to move their colonies from one area to another in search of better nectar and pollen resources. This may lead to concentrations of apiaries in limited areas, regardless of population density and the carrying
capacity of the landscape (Durant, 2019; Henry & Rodet, 2018). Additionally, some beekeepers concentrate on only some areas in search of a few particular species of plants that provide the most desired honey types (Al-Ghamdi et al., 2016). Overstocking of colonies may lead to overgrazing of floral resources by apiaries, negatively impacting native bee species. One study even suggests that high density beekeeping can reduce nectar and pollen harvesting by the honey bees themselves (Henry & Rodet, 2018). For example, beekeepers in North Dakota from 1976 to 1978 averaged around 116 lbs per colony of honey and in 2018 the average was close to 76 lbs due to overstocking of colonies (Durant, 2019). Regarding U.S. public land, no directive exists to determine the number of honey bee colonies to be placed per unit area, nor is there an established minimum distance between two adjacent apiaries to minimize competition caused by the overlapping of foraging ranges and subsequent decline of productivity of colonies.

Some studies have used models to determine the pressure on floral resources through analysis of carrying capacity of hives (Al-Ghamdi et al., 2016), the impact of spatial configuration (Henry et al., 2012), and spatial models for mapping monthly production of nectar and pollen from land cover maps (Ausseil et al., 2018). Land managers and beekeepers are eager to determine and use a carrying capacity for bees in the landscape (Wojcik et al., 2018). However, this is a challenge because climate, soil, and other variables impact the number of bee species and the dynamics of pollen and nectar availability (Wojcik et al., 2018). Additionally, pollen and nectar recharges daily and is commonly overproduced as an evolutionary strategy (Wojcik et al., 2018).

Honey bees are a significant contributor to U.S. agricultural security because of the pollination services they provide. Native bees provide essential ecological functions and pollination services that can provide insurance against honey bee losses (Durant, 2019). The availability of healthy bee forage is important for both commercial honey bees and native bees. There is a critical need to develop monitoring tools to estimate floral resources for bees in natural...
landscapes, prior to recommendations for habitat management. Quantifying flowers is typically done using ground-based sampling designs such as linear transects or quadrat sampling, which offer high resolution data. However, due to the time and labor costs associated with manual sampling, many floral samples capture only a fraction of the areas relevant to pollination. In diverse landscapes these limited sampling methods may not adequately capture spatial and temporal variation of floral resources that can be accessed by bees. As a result, local floral communities may be poorly described, leading to weak conclusions on landscape patterns and trends. Furthermore, the wide range of manual sampling methods used by ecologists are often not reported in sufficient detail, leading to a lack of standardized sampling methods (Szigeti et al., 2016).

Unmanned aerial vehicles (UAVs) offer a solution to sampling scale and reproducibility. Drones are frequently being used by ecologists to address questions involving vegetation communities and habitat assessments. These platforms can collect high resolution imagery that can be easily archived for future analyses (Barnas et al., 2019). Furthermore, flight paths are highly repeatable over areas of interest which allows users to conduct repeated surveys with minimal variation (Barnas et al., 2019). Recent advances in sensors and UAV platforms provide opportunities to estimate available floral resources for honey bees and native bees on a landscape scale using digital imagery.

Before unmanned aerial systems (UAS), remote sensing for vegetation mapping relied on satellite imagery or low-resolution aerial imagery. Images are used to measure crop production over the season and for identifying landscape trends with land cover and land use classification maps. These methods offer large spatial coverage, but miss fine scale data such as species assemblages or plant demographic information (Barnas et al., 2019). The quality of the satellite imagery is also affected by atmospheric conditions such as cloud cover, resolution, and passover frequency, potentially limiting the repeatability of image acquisition and appropriate timing to
address rapid landscape changes (Barnas et al., 2019). However, the commercial development of
UAVs equipped with high resolution sensors and navigational software enabled automated flights
make it possible to fly low altitudes where the atmosphere has a decreased effect on imagery and
it is possible to capture very high spatial resolutions for floral resource mapping (Xavier et al.,
2018). UAVs coupled with machine learning classifications could be a valuable tool in estimating
available floral resources for bees on a landscape scale.

The available floral resources in an ecosystem are one of the most important factors in
supporting bee diversity and abundance (Potts et al., 2003). Previous research suggests a high
diversity and abundance of floral resources will support a high diversity and abundance of insect
consumers (Potts et al., 2003). UAVs may not only be valuable in estimating floral resources for
bees, but also in predicting the associated bee community structure. UAVs may prove to be an
efficient tool for floral resource sampling and bee community sampling in non-agricultural
landscapes. With my research I aim to support apiarists and land managers by providing an
efficient method to quantify available floral resources for bees and predict the associated bee
community to aid in apiary placement in natural landscapes. It is my expectation to identify the
relationship between floral resources and bee community structure using UAV technology and
machine learning classification.

There are two main objectives of my research: 1) Characterize floral resource availability
for bees using unmanned aerial vehicle (UAV) imagery and machine learning classification
analysis, and 2) Determine the relationship between available floral resources and bee community
structure in USDA Forest Service Cache National Forest. Specifically, I examine the composition
of the landscape using an assortment of land cover classes and floral resource classes created
from UAV imagery. I use and compare two floral resource sampling methods: UAV data
collection and field-based ground transect collection methods. Furthermore, I compare the
classification model output to a test dataset compiled from the UAV imagery. With my research I
aim to determine the utility of UAVs for sensing and classifying flowers in non-agricultural landscapes. Furthermore, I aim to provide a link between floral resource availability and the pollinator community. This framework may identify aspects of the landscape that predict floral productivity and bee community structure, which will enable stakeholders to effectively manage apiary locations while also considering the needs of native bee species. Without an efficient framework to identify floral resource availability of bee pasture, efforts to promote conservation and commercial success will remain ineffective.
Literature Cited


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https://doi.org/10.1111/ele.12659


CHAPTER TWO

Quantifying floral resource availability using unmanned aerial systems and machine learning classifications

Abstract

Flowers provide many ecosystem services, namely food for insects, via the plant pollinator relationship. Manual methods to characterize flowering vegetation is costly in time and personnel. In diverse landscapes these limited methods may not adequately capture the spatial and temporal variation of floral resources that can be accessed by bees. Recent advances in sensors and unmanned aerial vehicle (UAV) platforms offer opportunities to characterize the dynamic distribution of floral resources at the landscape level. In the present study, UAV imagery and a multi-model machine learning classification analysis were used to quantify floral resources for bees in non-agricultural environments, where topography, vegetation, and flower inflorescence size are variable. Seven flower species totaling 2,137.96 m² of floral area were classified throughout the study, equaling 0.5% of the overall classified landscape. Based on the dynamic changes of floral area classified in UAV images, it was determined that the period of flowering and changes of flower coverage for different species varied. Models performed well considering the extreme rarity of flowers in the UAV images. Average sensitivity and specificity for the flower classes throughout the study were 0.77 and 0.99 respectively. The use of UAVs appears to be a feasible method for characterizing floral resources in non-agricultural settings. Classifications would benefit from a more robust and comprehensive UAV sampling plan, to better characterize the variability of floral resources in UAV imagery through increased sample sizes across a variety of habitats, floral phenology, and light variation.
Introduction

Unmanned aerial vehicles (UAVs) are frequently being tested in a diversity of applications. UAVs can operate at low altitudes, providing aerial imagery with exceptional spectral, spatial, and temporal resolutions, allowing detection of fine details of vegetation (Maes & Steppe, 2019). Recent advances in platforms and sensors have enabled users to accurately map the landscape to better understand and manage agriculture and the environment. Compared to ground surveys, UAVs can cover large areas in a relatively short amount of time, capturing spatial variation in vegetation communities allowing for a more concise picture of local ecosystem processes and habitat assessments (Barnas et al., 2019). These platforms can rapidly collect high resolution imagery that can be easily archived for future analyses, and flight paths are highly repeatable over areas of interest, which allows users to conduct repeated surveys with minimal spatial variation across flights (Barnas et al., 2019).

UAVs are used extensively in precision agriculture to direct management practices to specific areas, allowing farmers to use within-field spatial variation data to their advantage (Maes & Steppe, 2019). This leads to reduced inputs (e.g., fertilizer, herbicides, seed, and fuel) while yield is maintained or increased (Mulla, 2013). UAVs are used to detect drought stress and develop precise irrigation schedules (Ding, 2019). UAVs enable farmers to track severity of infection by pathogens and insects and target specific areas with pesticides (Gennaro et al., 2016; Sugiura et al., 2016). For example, Chen et al., (2021) used a UAV to determine position of fruit tree pests in real time to target pesticide spraying. Weed detection from UAV is an important application in precision agriculture, enabling farmers to develop prescription maps for herbicide spraying (Tamouridou et al., 2017). Recent studies suggest that UAVs may be used to estimate chlorophyll or nitrogen levels in crops through measuring of leaf or canopy reflectance (Maresma et al., 2016; Schirrmann et al., 2016). Within field growth vigor and biomass may be estimated with UAVs, allowing farmers to monitor crop growth, predict yield, and plan further management.
(Chu et al., 2016; Du & Noguchi, 2017; Gracia-Romero et al., 2017; Schirrmann et al., 2016). For example, analysis of UAV based normalized difference vegetation index (NDVI) imagery yielded higher accuracy of vineyard crop vigor when compared to Sentinel 2 satellite based NDVI imagery (Khaliq et al., 2019).

In recent years, UAVs have become frequently used in ecological monitoring. UAVs equipped with high resolution sensors have rendered many small objects identifiable, specifically flowers. Flower production is essential for the survival of many plant species because it relates directly to the number of seeds produced (Carl et al., 2017). Flowers provide many ecosystem services, namely food for insects, via the plant-pollinator relationship (Potts et al., 2003). Furthermore, resulting fruits and seeds are relied on by many animals. Therefore, the ability to quantify flowers using UAVs may provide an important indicator for biodiversity and may inform decisions on habitat management.

Many studies have identified flowers in the landscape with UAVs. Wan et al., (2018) detected and estimated flower number of oilseed rape using UAV based vegetation indices and image classification with high accuracy. A recent study demonstrated that UAVs can accurately detect sorghum panicles to estimate flowering time (Cai et al., 2021). One study estimated apple tree blossoms using UAV imagery to optimize the thinning of apple trees to increase fruit quality (Tubau Comas et al., 2019). Additionally, by mapping the flowering of invasive shrub Acacia longifolia (Fabaceae), UAVs were used to monitor the effect of biocontrol agents on invasive population (de Sá et al., 2018). Another study showed that UAV remote sensing has a high potential for performing detailed surveys of hedgerow flowers to inform decisions on habitat management and biodiversity conservation (Smigaj & Gaulton, 2021). UAVs were used to estimate arthropod populations based on corresponding floral resources (Xavier et al., 2018). Finally, one study in Germany estimated food resources for the European honey bee, Apis mellifera, by using a UAV to count Robinia pseudoacacia (Fabaceae) flowers (Carl et al., 2017).
The majority of studies are in controlled plots or agricultural areas where conditions are mostly homogenous. Furthermore, most studies focus on only one flower species. Research is limited in non-agricultural environments, where topography, vegetation, and flower inflorescence size are variable.

As demonstrated by Xavier et al., (2018) and Carl et al., (2017) UAVs may be a valuable tool in estimating floral resources available to flower visiting insects such as pollinators. Land use change through development and agricultural intensification have caused a reduction in floral resources for wild and managed bee populations. The lack of floral resources has created a need to find additional bee pastures for the commercial honey bee keeper. Images collected by UAVs offer opportunities to create broad regional surveys of floral resources which will enable stakeholders to effectively manage apiary locations.

In the present study, I use a UAV and machine learning classification analysis as an innovative and economical option to quantify floral resources in a montane landscape managed by the U.S. Forest Service. Specifically, I aim to quantify available floral resources for commercial apiaries and wild bee pollinators in three, nine-acre study areas using UAV imagery. I quantify the phenology of seven different wildflowers, across four time series during the summer season. I examine the composition of the landscape using an assortment of land cover classes and floral resource classes present in UAV imagery.

The goal of this research is to demonstrate a method to quantify floral resources in a non-agricultural landscape available to commercial apiaries and wild bee pollinators. This study represents a first step to analyze wild flower abundance, diversity, and phenology across variable topography using UAVs. The research objectives of this study are (1) capture high spatial resolution UAV imagery across USDA Forest Service Cache National Forest, (2) develop and test a multiple stage machine learning algorithm that extracts floral resource features, and (3) assess spatial temporal variation in floral resources at three field sites. The results of this research will
provide land managers and apiarist methods to inform availability of wildflower resources to support wild and managed bee species in montane environments and heterogeneous landscapes.

Methods

Study Area

Three field sites were established within USDA Forest Service Cache National Forest in close proximity to commercial apiaries across the semiarid foothills of Bear River Range in Northern Utah: Blacksmith Fork Canyon Road (BF), Franklin Basin Road (FB), and Twin Creek Road (TC) (Figure 2.1, Table 2.1). The mean elevation for the field sites is 2082 m AMSL. The average daily high temperature during the warm season is above 26°C, with the hottest month of the year in July. Elevation data, precipitation, average maximum temperature, and average minimum temperature at each field site were downloaded from NASA Earth Data (https://appeears.earthdatacloud.nasa.gov/). See Table 2.2 for weather conditions at the field sites throughout the length of the study. Managed cattle were sometimes present at the field sites. The study areas consist of mostly *Artemisia* (Asteraceae), *Populus* (Salicaceae), *Juniperus* (Cupressaceae), and *Pseudotsuga* (Pinaceae).

<table>
<thead>
<tr>
<th>Field Site</th>
<th>Lat/Lon</th>
<th>Elevation</th>
<th>Slope</th>
<th>Aspect</th>
</tr>
</thead>
<tbody>
<tr>
<td>BF</td>
<td>41°41'14.23&quot;N, 111°27'45.70&quot;W</td>
<td>2,214 m</td>
<td>6.93</td>
<td>310.85</td>
</tr>
<tr>
<td>FB</td>
<td>41°57'8.94&quot;N, 111°35'2.35&quot;W</td>
<td>2,122 m</td>
<td>3.43</td>
<td>128.35</td>
</tr>
<tr>
<td>TC</td>
<td>41°51'50.04&quot;N, 111°34'36.47&quot;W</td>
<td>1,910 m</td>
<td>9.01</td>
<td>153.52</td>
</tr>
</tbody>
</table>

Figure 2.1

Apiary Field Sites

Note: Apiary field sites located in USDA Forest Service Cache National Forest across the semiarid foothills of Bear River Range in Northern Utah: Blacksmith Fork Canyon Road (BF), Franklin Basin Road (FB), and Twin Creek Road (TC). (Google Earth Pro version 7.3.4.8642).
### Table 2.2

Weather Events Between Sampling Events at the Field Sites

<table>
<thead>
<tr>
<th>Field Site</th>
<th>Total Precipitation in between sampling events (mm)</th>
<th>Average maximum temperature in between sampling events (°C)</th>
<th>Average minimum temperature in between sampling events (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BF1</td>
<td>32.59</td>
<td>16.95</td>
<td>3.76</td>
</tr>
<tr>
<td>BF2</td>
<td>11.29</td>
<td>25.38</td>
<td>10.52</td>
</tr>
<tr>
<td>BF3</td>
<td>38.61</td>
<td>26.08</td>
<td>12.44</td>
</tr>
<tr>
<td>BF4</td>
<td>47.54</td>
<td>23.04</td>
<td>9.07</td>
</tr>
<tr>
<td>BF Total</td>
<td>130.03</td>
<td>Average: 22.86</td>
<td>Average: 8.95</td>
</tr>
<tr>
<td>FB1</td>
<td>0</td>
<td>24.56</td>
<td>8.99</td>
</tr>
<tr>
<td>FB2</td>
<td>0</td>
<td>28.47</td>
<td>12.01</td>
</tr>
<tr>
<td>FB3</td>
<td>50.06</td>
<td>26.66</td>
<td>12.22</td>
</tr>
<tr>
<td>FB4</td>
<td>51.4</td>
<td>23.24</td>
<td>9.03</td>
</tr>
<tr>
<td>FB Total</td>
<td>101.46</td>
<td>Average: 25.73</td>
<td>Average: 10.56</td>
</tr>
<tr>
<td>TC1</td>
<td>0</td>
<td>26.47</td>
<td>9.49</td>
</tr>
<tr>
<td>TC2</td>
<td>0</td>
<td>30.003</td>
<td>12.44</td>
</tr>
<tr>
<td>TC3</td>
<td>39.85</td>
<td>28.29</td>
<td>12.92</td>
</tr>
<tr>
<td>TC4</td>
<td>42.64</td>
<td>25.49</td>
<td>9.83</td>
</tr>
<tr>
<td>TC Total</td>
<td>82.49</td>
<td>Average: 27.56</td>
<td>Average: 11.17</td>
</tr>
</tbody>
</table>

*Note: Time series one data is based on the prior 30-days. (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek). Accessed from AppEEARS (https://appeears.earthdatacloud.nasa.gov/, Accessed: 29 June 2022).*
Floral vegetation training data field survey

For the classification workflow, training data is needed to teach the algorithm how to recognize the different classes in the image. Non-flowering vegetation, soil, and trees are large enough to be easily recognized within the UAV images. However, because many of the inflorescences were ~2 cm in diameter and more difficult to identify in the imagery, locations of the flowers were needed to establish training data for the classification algorithm during analysis. For this reason, training data was established in the field before each flight by placing numbered orange 12-inch bucket lids next to multiple unique flower species and recording each point location with a GPS (Figure 2.2). Additionally, a photo was taken on the ground with an off the shelf RGB camera to aid in recognizing the flowers in the imagery. The GPS points and orange bucket lids were used to identify the different flower species and create training data in the UAV imagery.
Figure 2.2

Photos of Flower Species in the Current Study

Achillea millefolium  Agastache urticifolia  Ericameria nauseosa  Potentilla grandulosa

Eriogonum heracleoides  Geranium viscosissimum  Senecio serra

Note: Seven classified flower species: Achillea millefolium (Asteraceae), Agastache urticifolia (Lamiaceae), Ericameria nauseosa (Asteraceae), Potentilla glandulosa (Rosaceae), Eriogonum heracleoides (Polygonaceae), Geranium viscosissimum (Geraniaceae), and Senecio serra (Asteraceae). Orange 12-inch bucket lids were placed next to individual flower species to aid in identification in the UAV imagery during analysis.
**UAV Flights**

Remotely sensed images were acquired by the WingtraOne, a fixed wing, vertical takeoff and landing (VTOL) UAV. The WingtraOne was equipped with a 35mm focal length, Sony RX1RII RGB 42MP camera, with a sensor size of 7952 x 5304 pixels. The WingtraOne was flown over each field site four times over the Summer of 2021 (Table 2.3). This resulted in a total of 12 orthomosaic images. My objective was to capture floral resources at approximately the beginning, middle, and end of the summer season. All flights were completed within two hours of solar noon to reduce inconsistencies due to sun angle. The weather was sunny without much wind. Camera exposure time was set to 1/2000 with 160 ISO and an aperture of 5.0. To achieve good image stitching performance, forward and side overlaps were 64% and 70% respectively. Considering the highly variable and steep terrain, flights were preprogrammed to observe a specific flight plan perpendicular to slope while following terrain at 52 meters above ground level to provide a 1cm$^2$ ground resolution per pixel. Average flight time was ~ 20 minutes. Data was written to an SD card and processed at the USDA SCINet CERES (https://scinet.usda.gov/) remote computing cluster.

<table>
<thead>
<tr>
<th>Field site</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twin Creek flights</td>
<td>6/29/2021</td>
<td>7/14/2021</td>
<td>8/7/2021</td>
<td>8/24/2021</td>
</tr>
</tbody>
</table>

*Note: WingtraOne flight schedule to capture floral resource availability. The WingtraOne captured imagery four times at each field site (Time series: T1, T2, T3, T4).*
Orthomosaic processing

All flight data were processed using the open-source software OpenDroneMap (ODM) (OpenDroneMap project (http://opendronemap.github.io/odm/) using the USDA SCINet CERES (https://scinet.usda.gov/) remote computing cluster. ODM orthomosaic feature quality and point cloud quality were both set to “high”. These parameters resulted in output data with an average spatial resolution of 1 cm². The resulting output orthomosaics were prepared for classification in the R statistical software version 4.1.3 (R-core team, 2022). To make processing times quicker, flight areas were clipped to 9 acres (3.65 hectares) surrounding the minimum common boundary across all images using the gdalUtils R package. Objects such as vehicles were clipped/removed out of the image. To ensure spatial accuracy across time series, images from each field site were spatially rectified in ArcGIS Pro version 2.8.0. The first time series from each field site served as the master image, which all subsequent imagery were rectified to match.

Vegetation Indices

The use of vegetation indices (VIs) instead of reflectance is common in remote sensing studies because they minimize the influence of distorting factors, such as the elevation angle of the sun, and the atmosphere (García-Fernández et al., 2021; Wan et al., 2018). In this study 13 VIs were selected from the literature (Table 2.4). The following VIs were created from RGB images using the open source R statistical software version 4.2.0 (R-core team, 2022): Simple blue-green ratio (BGI) reflecting chlorophyll content and vigor (Zarcot ejada et al., 2005), color index of vegetation (CIVE) (Kataoka et al., 2003), enhanced bloom index (EBI) (B. Chen et al., 2019), normalized green-blue difference index (NGBDI) that reflects visualization of changes in growth states (Du & Noguchi, 2017), normalized green red difference index (NGRDI) (Gitelson et al., 2002; Tucker, 1979), modified green red vegetation index (MGRVI) and RGB-based vegetation index (RGBVI) reflecting vine vigor and biomass (Bendig et al., 2015), RGB-based
vegetation index 2 (RGBVI2) and RGB-based vegetation index 3 (RGBVI3) which were created on the basis of different combinations of RGB bands (García-Fernández et al., 2021), red-green ratio index (RGRI) (Gamon & Surfus, 1999; Verrelst et al., 2008), visible band difference vegetation index (VDVI) (Wan et al., 2018), excess green index (ExG) and vegetative (VEG) that automatically detects areas related to bare soil, weeds, residues (Matese et al., 2018), and water stress conditions (D. M. Woebbecke et al., 1995; Hague et al., 2006; Jiménez-Brenes et al., 2019). These VIs were used as inputs into the classification algorithm.
### Table 2.4

**Thirteen Vegetation Indices**

<table>
<thead>
<tr>
<th>Indices</th>
<th>Definition</th>
<th>Citation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple blue-green ratio (BGI)</td>
<td>B / G</td>
<td>Zarcotejada et al., 2005</td>
</tr>
<tr>
<td>Color index of vegetation (CIVE)</td>
<td>(0.441 \times R - 0.881 \times G + 0.385 \times B + 18.787)</td>
<td>Kataoka et al., 2003</td>
</tr>
<tr>
<td>Enhanced bloom index (EBI)</td>
<td>((R + G + B) / (G / B)^*(R − B + 256))</td>
<td>Chen et al., 2019</td>
</tr>
<tr>
<td>Excess green index (ExG)</td>
<td>((2 \times G – R - B))</td>
<td>Matese et al., 2018</td>
</tr>
<tr>
<td>Modified green red vegetation index (MGRVI)</td>
<td>((G^2 – R^3) / (G^2 + R^2))</td>
<td>Bendig et al., 2015</td>
</tr>
<tr>
<td>Normalized green-blue difference index (NGBDI)</td>
<td>((G - B) / (G + B))</td>
<td>Du &amp; Noguchi, 2017</td>
</tr>
<tr>
<td>Normalized green red difference index (NGRDI)</td>
<td>((G - R) / (G + R))</td>
<td>Gitelson et al., 2002</td>
</tr>
<tr>
<td>RGB-based vegetation index (RGBVI)</td>
<td>(G^2 - (B \times R) / G^2 + (B \times R))</td>
<td>Bendig et al., 2015</td>
</tr>
<tr>
<td>RGB-based vegetation index 2 (RGBVI2)</td>
<td>((G - R) / B)</td>
<td>García-Fernández et al., 2021</td>
</tr>
<tr>
<td>RGB-based vegetation index 3 (RGBVI3)</td>
<td>((G + B) / R)</td>
<td>García-Fernández et al., 2021</td>
</tr>
<tr>
<td>Red-green ratio index (RGRI)</td>
<td>(R / G)</td>
<td>Gaman &amp; Surfas, 1999; Verrelst et al., 2008</td>
</tr>
<tr>
<td>Visible band difference vegetation index (VDVI)</td>
<td>((2 \times G – R - B) / (2 \times G + R + B))</td>
<td>Wan et al., 2018</td>
</tr>
<tr>
<td>Vegetative (VEG)</td>
<td>(G / (R^{0.667} \times B^{1-0.667}))</td>
<td>Matese et al., 2018</td>
</tr>
</tbody>
</table>

*Note: Thirteen vegetation indices (VIs) selected from the literature and created using RGB bands.*
Texture Covariates

Texture covariates were created in the R statistical software version 4.2.0 (R-core team, 2022) using the *GLCM_textures* R package (https://github.com/ailich/GLCMTextures). This package calculates the most common grey-level co-occurrence matrix (GLCM) texture metrics used for spatial analysis (Hall-Beyer, 2017). GLCM textures considers the relationship, or “texture” between two pixels at a time, called the reference and the neighbor pixel. Texture metrics are calculated using a symmetric GLCM, meaning each pixel is counted as a focal and a neighboring pixel. The texture measure calculation to a GLCM is limited to extremely small areas on the image. This calculation is repeated across the entire image and assigns a number to represent different textures in each pixel. This gives the pixel-to-pixel relationships across the entire image. In this study I used seven texture covariates to separate the flowers from the surrounding vegetation (Table 2.5). I created the following seven texture covariates: The contrast group: GLCM Contrast, GLCM Dissimilarity, GLCM Homogeneity. The orderliness group: GLCM Angular Second Moment (ASM) and GLCM Entropy. The descriptive statistics group: GLCM Mean and GLCM Variance. These texture covariates were used as input into the classification algorithm.
Table 2.5  

*Seven Texture Covariates*

<table>
<thead>
<tr>
<th>Group</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Contrast</strong></td>
<td>GLCM Contrast $= \sum_{i,j=0}^{N-1} P_{i,j} (i - j)^2$</td>
</tr>
<tr>
<td></td>
<td>GLCM Dissimilarity $= \sum_{i,j=0}^{N-1}</td>
</tr>
<tr>
<td></td>
<td>GLCM Homogeneity $= \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1 + (i - j)^2}$</td>
</tr>
<tr>
<td><strong>Orderliness</strong></td>
<td>GLCM Angular Second Moment (ASM) $= \sum_{i,j=0}^{N-1} P_{i,j}^2$</td>
</tr>
<tr>
<td></td>
<td>GLCM Entropy $= \sum_{i,j=0}^{N-1} P_{i,j}[-ln(P_{i,j})]$ where $0 * ln(0) = 0$</td>
</tr>
<tr>
<td><strong>Descriptive statistics</strong></td>
<td>GLCM Mean($\mu$) $= \sum_{i,j=0}^{N-1} i(P_{i,j})$</td>
</tr>
<tr>
<td></td>
<td>GLCM Variance($\sigma^2$) $= \sum_{i,j=0}^{N-1} P_{i,j}(i - \mu)^2$</td>
</tr>
</tbody>
</table>

*Note: Seven texture covariates were created using the GLCM_textures R package. (https://github.com/ailich/GLCMTextures). GLCM textures considers the relationship, or “texture” between two pixels at a time. This gives the pixel-to-pixel relationships across the entire image.*
**Floral vegetation training data creation**

Before classification, the VIs and texture covariates were rescaled from 32-bit float to 8-bit to decrease file sizes in the R statistical software version 4.2.0 (R-core team, 2022). Twenty-three covariates were compiled into a single raster composite (3 RGB, 7 textures, 13 VIs). The training dataset was built with polygons that were manually delineated in the raster composite, based on visual interpretation using the ground photos, GPS locations, and orange bucket lids as reference. Locating training data in the imagery was influenced by morphology and abundance of inflorescences. Confident training samples were created only if there was no uncertainty about class identification. Polygons were spread across the extent of the orthomosaic to capture spectral variability of classes. Training samples were established for 7 flower species: *Achillea millefolium* (Asteraceae), *Agastache urticifolia* (Lamiaceae), *Ericameria nauseosa* (Asteraceae), *Eriogonum heracleoides* (Polygonaceae), *Geranium viscossimum* (Geraniaceae), *Potentilla glandulosa* (Rosaceae), *Senecio serra* (Asteraceae). (Figure 2.2). The `exactextractr` version 0.8.2 R package was used to extract individual pixel values that were overlaid by the training polygons. The individual pixel values were used to train the classifier.

**Random Forest Classification**

Flowers were classified using a random forest (RF) classifier. The processing was performed in R using the `randomForest` package version 4.7-1. Training samples were split into training and test datasets. Seventy percent of the samples were used to train the RF algorithm and thirty percent of the samples were used to test the RF algorithm. \textit{Mtry} is the number of variables randomly sampled as candidates at each split. The \textit{Mtry} that produced the lowest out of box (OOB) error was determined using the `tuneRF()` function in the `randomForest` R package. The lowest OOB error \textit{mtry} and 500 trees were used for each RF algorithm.
Initial RF models were constructed using all 23 covariates (3 RGB, 7 textures, 13 VIs). The mean decrease in accuracy (MDA) metric was used to measure covariate contribution in the models. Mean decrease in Accuracy plots are given in Appendix A, Figure A.1 – A.42. In the initial RF models no single type of covariate consistently performed high so to reduce multicollinearity, the top two contributing covariates from RGB, textures, and VIs were chosen for the final RF models. This resulted in 6 covariates used in the final RF models (Appendix A, Figure B.4 – B.6). Two unique RF algorithms were used to classify each of the 12 images resulting in 24 total RF algorithms: The first RF was performed on three chosen classes: A flower class, vegetation, and soil. The generated RF model was used to classify the orthomosaic and create a land cover prediction map. All present flower species were combined in one single flower class in the land cover classification model to reduce model complexity and reduce influence of similar spectral characteristics between classes. The flower class in the land cover prediction map was masked and a second RF was performed on the masked flower class to separate the flower class into individual species. Across all 12 images 7 flower species were classified: *A. millefolium*, *G. viscossimum*, *P. glandulosa*, *E. heracleoides*, *A. urticifolia*, *S. serra*, and *E. nauseosa*. The generated RF model was used to classify the orthomosaic and create a floral prediction map. The land cover prediction map and the floral prediction map were merged into a final prediction map using ArcGIS Pro version 2.8.0.

Flower detection performance was assessed by applying the RF model to the test data set. For validation against the test data set a confusion matrix was computed, producing in class sensitivity and specificity. Sensitivity refers to the model’s ability to predict true positives of each available category. Specificity refers to the model’s ability to predict true negatives of each available category. Scores closer to 1 indicate high sensitivity/specificity, whereas values closer to 0 indicate low sensitivity/specificity. In each nine-acre (3.65 ha) classification prediction map, floral area was calculated for each species. The images throughout the study maintained a pixel
size resolution of 1 cm². Floral areas were converted to m². Floral area was used as a measure of floral abundance at the field sites.

Results

Random forest covariate importance

The red band covariate was retained in 20 out of 24 final RF models making it the most used covariate across all models because of its high contribution in the initial RF models (Table 2.6 – 2.7). GLCM Mean, green, GLCM Variance, CIVE, and NGBDI covariates were also retained in many of the final models based on their initial RF contribution. In contrast, the NGRDI, RGBVI, BGI, and VDVI covariates were retained in only 2 out of 24 models making these covariates the least used covariates across all final models because of the low contribution in the initial RF models. CIVE was the most important covariate across all models with an average mean decrease accuracy of 153.61, followed closely by NGBDI with an average mean decrease accuracy of 143.46. The least important covariates across all models were NGRDI and RGBVI with an average mean decrease accuracy of 20.31 and 27.36 respectively.

Across all land cover classification models the covariate with highest importance was NGBDI with a mean decrease accuracy of 235.81, followed by CIVE with a 170.45 mean decrease accuracy (Table 2.6). The least important covariates across all land cover classification models were RGBVI and the green band with an average mean decrease accuracy of 34.0248 and 41.94 respectively. EBI was the most important covariate across all flower classification models with a mean decrease accuracy of 91.23 followed by NGBDI with 88.05 (Table 2.7). In contrast, GLCM dissimilarity and GLCM variance were the least important covariates across all flower classification models with a mean decrease accuracy of 0.93 and 3.03 respectively.
Table 2.6

*Land Cover Classification Covariate Importance Table*

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<th>BF2</th>
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*Note:* The mean decrease in accuracy (MDA) metric was used to measure covariate contribution in the model (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek).
Table 2.7

*Flower Classification Covariate Importance Table*

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*Note:* The mean decrease in accuracy (MDA) metric was used to measure covariate contribution in the model (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek).
Random forest sensitivity and specificity

The random forest specificity was constantly high in all the models. However, the random forest sensitivity fluctuated. In the land cover classifications, the average sensitivity and specificity of the flower class across all sites and time series was 0.77 and 0.99 respectively (Figure 2.3, Table 2.8). In the land cover classifications, the average sensitivity and specificity of the vegetation class across all sites and time series was 0.98 and 0.98 respectively. In the land cover classifications, the average sensitivity and specificity of the soil class across all sites and time series was 0.97 and 0.97 respectively. In the land cover classifications, average flower class sensitivity was the highest at the Blacksmith Fork field site with 0.91 across time series, followed by Twin Creek flower class with 0.68, and the lowest average flower class sensitivity at the Franklin Basin site with 0.57. Flower class sensitivity across all sites was highest in time series one with 0.82, then decreased to 0.74 in time series two, decreased again to 0.59 in time series three, and increased in time series four to 0.72.

The flower classes in the flower classification models produced high average sensitivity of 0.86 and high average specificity of 0.95. *Achillea millefolium* was the most prevalent species during the study and was classified in 10 different images across all 3 field sites. Average sensitivity for *A. millefolium* was 0.78, while average specificity was 0.95 indicating an overall good predictive accuracy. However, *A. millefolium* had poor sensitivity, as demonstrated by sensitivity values of below 0.5 twice throughout the study: 0.2 at Franklin Basin time series three and 0.42 at Blacksmith Fork time series three. *Geranium viscossimum* was present in Twin Creek and Franklin Basin field sites across five images. Average sensitivity for *G. viscossimum* was 0.89, while average specificity was 0.94 indicating an overall excellent predictive accuracy. *Potentilla glandulosa* was found in Twin Creek and Franklin Basin field sites across four images. Average sensitivity for *P. glandulosa* was 0.97, while average specificity was 0.98 indicating an overall excellent predictive accuracy. *Eriogonum heracleoides* was classified once at the Twin
Creek field site and once at the Franklin Basin field site. Average sensitivity for *E. heracleoides* was 0.89, while average specificity was 0.99 indicating an overall excellent predictive accuracy. *Agastache urticifolia* was classified in three images at the Blacksmith fork field site. Average sensitivity for *A. urticifolia* was 0.84, while average specificity was 0.93 indicating an overall excellent predictive accuracy. *Senecio serra* was found in Franklin Basin and Blacksmith fork field sites across four images. Average sensitivity for *S. serra* was 0.92, while average specificity was 0.97 indicating an overall excellent predictive accuracy. *Ericameria nauseosa* had the best sensitivity and specificity of all flower classes and was found once at the Blacksmith Fork field site. Average sensitivity for *E. nauseosa* was 0.98, while average specificity was 0.99 indicating an overall excellent predictive accuracy.
Figure 2.3

Bar Plot of Average Within Class Sensitivity and Specificity Accuracy for Random Forest Models

Note: Sensitivity refers to the model’s ability to predict true positives of each available category. Specificity refers to the model’s ability to predict true negatives of each available category. Scores closer to 1 implicate high sensitivity/specificity, whereas values closer to 0 implicate low sensitivity/specificity.
### Table 2.8

**Average Within Class Sensitivity and Specificity Accuracy for Random Forest Models**

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<td>1 / 1</td>
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**Note:** Sensitivity refers to the model’s ability to predict true positives of each available category. Specificity refers to the model’s ability to predict true negatives of each available category. Scores closer to 1 implicate high sensitivity/specificity, whereas values closer to 0 implicate low sensitivity/specificity (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek).

* = refers to only one flower species in the model.
Floral Area

In total, 2137.96 m$^2$ of floral area were classified during the study across all field sites (Table 2.9, Figure 2.4). The Blacksmith Fork field site had the highest floral area throughout the study with 954.29 m$^2$, followed by the Twin Creek field site with 601.45 m$^2$, and the Franklin Basin field site with 582.21 m$^2$ of floral area. The highest floral area at one site was recorded on time series one at the Franklin Basin field site with 345.11 m$^2$. Time series 3 at the Twin Creek site produced the lowest amount of floral area with 40.53 m$^2$. Throughout the study a decrease of total flowers across all field sites was identified. In time series one the total floral area across all field sites was 859.22 m$^2$. This floral area decreased in time series two to 484.85 m$^2$. In time series three and four the floral area decreased to 470.66 m$^2$ and 323.22 m$^2$ respectively. In some time series, low abundance of flowers in the landscape resulted in insufficient training sample numbers for classification.

*Achillea millefolium* was prevalent at all three field sites throughout the study with an average floral area of 241.58 m$^2$. *Geranium viscossimum* and *P. glandulosa* were classified at Twin Creek and Franklin Basin field sites with an average floral area of 121.09 m$^2$ and 15.19 m$^2$ respectively. *Eriogonum heracleoides* was classified at two field sites with different areas. Time series three Franklin Basin field site was classified with 3.38 m$^2$ of *E. heracleoides* and Franklin Basin field site was classified with 271.43 m$^2$ of *E. heracleoides*. *Agastache urticifolia* and *S. serra* were prevalent across 3 time series at Blacksmith Fork field site with an average floral area of 155.96 m$^2$ and 54.09 m$^2$. *Senecio serra* was also classified once at the Franklin Basin field site with 8.7 m$^2$ of floral area in the image. Finally, *E. nauseosa* was classified once at time series 4 in Blacksmith Fork field site with 99.41 m$^2$ floral area. Please see figure 2.5 to see an example of the classification output representing floral area overlaid on the original orthomosaic image.
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<td>15.39</td>
<td>NA</td>
<td>NA</td>
<td>7.13</td>
<td>NA</td>
<td>9.34</td>
<td>13.70</td>
<td>NA</td>
</tr>
<tr>
<td><em>Eriogonum heracleoides</em> (Polygonaceae)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>271.43</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>3.38</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td><em>Agastache urticifolia</em> (Lamiaceae)</td>
<td>214.10</td>
<td>140.18</td>
<td>113.61</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td><em>Senecio serra</em> (Asteraceae)</td>
<td>73.99</td>
<td>39.78</td>
<td>39.81</td>
<td>NA</td>
<td>NA</td>
<td>8.70</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td><em>Ericameria nauseosa</em> (Asteraceae)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>99.41</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

*Note:* Floral area of seven flower species using machine learning classification analysis by field site and time series (m²). NA (not applicable) are field sites and time series when flower species was not able to be classified due to low abundance of flowers in the landscape resulting in insufficient training sample numbers (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek).
Figure 2.4

Floral Area Plots Through Time

Note: Plots show fluctuations in floral species through time for each field site.
Figure 2.5

Nine-Acre UAV Image of Blacksmith Fork Field Site Time Series Two

Quantifying floral resources using UAVs

Note: Two inset maps are located in the upper right. The left inset map is the original image. The right inset map is the original image with the classification output overlaid. The blue represents pixels the model determined are occupied by *A. urticifolia* (113.6 m²/9 acres) the red represents pixels the model determined are occupied by *S. serra* (39.8 m²/9 acres).
Discussion

**Importance of covariate ranking**

Covariate importance ranking was important for covariate selection and model simplification. Excessive covariates are prone to cause multi-collinearity and overfit models (Wan et al., 2018). Three RGB, seven texture, and 13 VI covariates were used in the initial RF models. However, only six covariates were chosen for the final RF models based on the mean decrease in accuracy metric (Table 2.6-2.7). CIVE was the largest contributor to the land cover classification models which were used to separate land cover in the images. CIVE originally was designed to identify green vegetation and has been suggested to be sensitive to canopy color without the influence of shaded sunlit conditions which may have resulted in the large contribution to the land cover classification (Wan et al., 2018). Furthermore, NGBDI which has been suggested to reflect visualization of changes in growth states was also a large land cover classification model contributor. These VIs are typically used to reflect changes of canopy greenness which suggests why they were the most important contributors to the land cover classification models.

In the flower classification models to delineate between specific flower species, EBI and NGBDI were the largest model contributors. EBI was developed to enhance the bloom spectral signature while weakening the background spectral signals from leaves and soil (Chen et al., 2019). EBI was originally developed using the spectral signature of white and pink almond flowers which usually has a relatively high reflectance in the visible spectrum above 30% (B. Chen et al., 2019). Because of its sensitivity to white flowers, this may have caused the high contribution to the flower classification models.
Random forest sensitivity and specificity

Land cover classification models and flower classification models both have overall high average sensitivity and specificity in the flower classes, suggesting high predictive accuracy. The accuracy of the classification of vegetation depends on the imagery coinciding with the period at which the phenological phase of vegetation is most recognizable (Müllerová, Bartaloš, et al., 2017). Additionally, flowers occupied only 0.5% of the overall landscape in the UAV images. Sensitivity fluctuated throughout the study whereas specificity was constantly high, indicating floral phenology and the rarity of the flower classes played a major role in classification accuracy of floral resources. Flower class sensitivity was highest in Blacksmith Fork field site over the course of the study which may be attributed to the largest amount of precipitation at that field site with 130 mm throughout the study. Precipitation may cause the inflorescences to display a stronger spectral signal, thus raising classification sensitivity.

_Achillea millefolium_ produced a sensitivity below 0.5 in two images indicating sometimes the model misidentifies this species in the UAV imagery. In fact, _A. millefolium_ had the lowest sensitivity of all flower classes with 0.2 at Franklin Basin in time series three, and the second lowest sensitivity of 0.42 at Blacksmith Fork time series three. These low accuracies occurred in August, when _A. millefolium_ was undergoing senescence and likely displaying a weakened spectral signal. This may have caused commission errors of _A. millefolium_ being misclassified as soil/rock. Low sensitivity of _A. millefolium_ may also have been caused by overexposure of the image, or smoke from a forest fire in proximity affecting the spectral signals captured by the UAV. The other six flower species had high sensitivity and specificity throughout the study. Given the whitish color of _G. viscossimum, A. urticifolia_, and _E. heracleoides_, EBI may be the reason for such high accuracy numbers because of its sensitivity to white flowers. Conversely, the yellow flowers _P. grandulosa, S. serra_, and _E. nauseosa_ may have benefited from EBI in separating yellow pixels from white pixels. Yellow flowers also had the highest average
specificity and sensitivity, whereas the white flowers were slightly lower indicating the more pronounced spectral signature from yellow flowers.

Implications and limitations

The UAV data collection, coupled with the multi-model image classification system, estimated the area occupied by extremely rare flower classes, and provided a metric to estimate floral resource abundance in non-agricultural environments, where topography, vegetation, and flower inflorescence size are variable. The research framework achieved moderate to high accuracy by using a multi-model random forest machine learning classification approach. I chose to use an RGB camera because flower canopy is prone to more reflections and less absorption between 500 nm and 700 nm (Yates & Steven, 1987). This was also a significant reduction of the camera equipment cost when compared to multispectral cameras. Furthermore, the spatial resolution of the Sony RX1RII RGB camera used in the study offered high resolution ~1cm² pixel size with the WingtraOne UAV, enabling identification of flowers in the imagery. However, due to the limited wavebands in RGB images, few studies have sought to utilize UAV based RGB camera data to estimate floral resources. However, by exploiting the RGB through creation of VIs and texture covariates I was able to accurately model floral resources at the field sites. Although floral resources are frequently measured, there exist few methods to efficiently quantify floral resources on a large scale. The use of UAVs appears to be a feasible approach for assessing floral resources in non-agricultural settings.

The flexibility in the acquisition of imagery with UAV allows capturing specific stages of phenology and in the present study, multiple flower species fluctuate in abundance throughout the study. This may be due to normal phenology, competition, or rain events throughout the season. Figure 2.4 demonstrates the changing inflorescence numbers throughout the summer season at the three field sites. Based on the dynamic changes of floral area classified in UAV RGB images, it
was determined that the period of flowering and changes of flower coverage for different species varied. *Achillea millefolium* floral area at Franklin Basin increased from time series two (33.38 m²/9-acres) to time series three (83.44 m²/9-acres) which may be attributed to 50.06 mm of precipitation between time series two and three (Table 2.2). *Agastache urticifolia* floral area at Blacksmith Fork decreased from time series one (214.1 m²/9-acres) to time series two (140.18 m²/9-acres) which may be attributed to a decrease in precipitation from 32.59 mm in 30 days before time series one to 11.29 mm in the 39 days before time series two (Table 2.2). Similarly, *S. serra* floral area at Blacksmith Fork decreased from time series one (73.99 m²/9-acres) to time series two (39.78 m²/9-acres) which may be attributed to the same precipitation pattern.

Additionally, the Blacksmith Fork models predict the highest overall abundance of flowers throughout the season. This may be due to the largest amount of precipitation at that field site with 130 mm throughout the study. Furthermore, of all three field sites, Blacksmith Fork has the highest elevation with 2,214 meters, and the lowest temperatures throughout the season. Blacksmith Fork field site is also the only field site located on a north facing slope which may enable this site to maintain its water more efficiently.

This study did not examine the spectral characteristics of flower blooms and how well the RGB camera was able to detect blooms under varying conditions of illumination. Furthermore, most blooms in the study happened to be white and yellow, which were easily detected with the RGB camera, so it is unknown how well the model would function with the detection of blooms emitting lower frequency ranges of the visible spectrum, such as blue and violet. Additionally, some time series did not have the floral abundance to create the appropriate amount of training data to classify some flower types. For example, *A. millefolium* was not prevalent enough to establish enough training data for classification at the Blacksmith Fork field site during time series two. However, it was very prevalent in time series one and time series three. Reasons for this may include the field technician not identifying enough flowers, or an extreme abundance of
another flower that outcompeted *A. millefolium* for that time series. Further research is needed to explore how the amount of training samples affect classification outcomes regarding floral resources.

This research was one of the first attempts to quantify multiple flower species using UAV technology in non-agricultural environments, where topography, vegetation, and flower inflorescence size are variable. The models developed in this study demonstrate a robust framework to measure abundance of flowering vegetation via UAV RGB aerial imagery. Overall, UAV based RGB images are promising for field phenotypic and phenological research in non-agricultural areas. Future research should focus on developing extensive libraries of training data, at various times of year and locations to build comprehensive models for multiple floral species. The quantification of flowers, fruits and other plant traits is of increasing importance to remote sensing of vegetation and thus the use of UAVs to monitor these resources should be investigated further.
Literature Cited


Chen, C.-J., Huang, Y.-Y., Li, Y.-S., Chen, Y.-C., Chang, C.-Y., & Huang, Y.-M. (2021). Identification of Fruit Tree Pests With Deep Learning on Embedded Drone to Achieve
https://doi.org/10.1109/ACCESS.2021.3056082

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https://doi.org/10.3389/fpls.2018.00293


OpenDroneMap Authors ODM – A command line toolkit to generate maps, point clouds, 3D models and DEMs from drone, balloon or kite images. OpenDroneMap/ODM GitHub Page 2020; https://github.com/OpenDroneMap/ODM


CHAPTER THREE

Can floral resource availability estimated by unmanned aerial vehicle imagery predict bee community structure?

Abstract

The landscape context is critical to understanding the relationship between floral resource availability and bee community structure. Prior studies suggest the structure of the bee community is dependent on floral diversity and floral abundance. Measuring the relationship between the floral and bee communities may enable apiarists and land managers to make informed decisions in managing wild and domesticated bee species. In the present study two data types were used to characterize floral resources in bee pasture: (1) Ground transect survey and (2) UAV imagery with machine learning classification analysis. I tested the hypothesis that increased bee diversity and abundance would positively correlate with increased floral diversity and abundance using seven simple linear regression models. I found that the floral resource data collected from ground transect surveys predicts bee diversity, bee richness, and bee abundance. I also found floral abundance data captured by UAV predicts bee abundance at the field sites. Finally, I found UAV floral abundance predicts ground transect floral abundance suggesting a positive relationship between different sampling methods. My results support previous research that suggests a high diversity of resources will support a high diversity of insect consumers, and habitats with abundant flowers have greater possibilities for partitioning of available resources. While five of the seven pairwise simple linear models were significant, the strength of the linear relationships were weak. Nonetheless, my results support UAVs as a feasible and efficient method for characterizing floral resources in non-agricultural settings. Further research should include using UAV imagery to quantify floral resources to predict bee community dynamics on a landscape scale.
Introduction

The distribution and abundance of floral resources are critical in shaping bee behavior and bee community structure. The availability of floral resources in an ecosystem are one of the most important factors in supporting bee diversity and abundance (Potts et al., 2003). Floral resources, specifically pollen and nectar are important because they support the reproduction and health of managed and wild bees (Döke et al., 2019; Donkersley et al., 2014; Horn et al., 2016; Sponsler & Johnson, 2015; Vaudo et al., 2015). Moreover, bees play an important role in providing ecosystem services by contributing directly to supporting angiosperm reproduction and persistence through pollination. Pollination services are essential to the functioning of natural and agricultural ecosystems and the global food supply. These pollination services are dependent on the spatial and temporal distribution of floral resources, which are dynamic across time and space.

Several studies have documented widespread declines in wild and managed bee populations (Hallmann et al., 2017; Seibold et al., 2019; van Klink et al., 2020; Woodard et al., 2020). Agricultural intensification and urbanization have caused a reduction in habitat (i.e., floral resources and nesting space) subsequently leading to inadequate nutrition available for bees (Cane & Tepedino, 2001; Hanberry et al., 2020; Otto et al., 2016a; Wojcik et al., 2018). Land use changes from grasslands to monoculture-based farming have also reduced the available floral resources (Durant, 2019; Goulson et al., 2015; Otto et al., 2016). Bees are especially susceptible to landscape changes (habitat degradation and habitat fragmentation) that lead to an increased spatial separation of suitable nesting sites and floral resources because bees are central place foragers and can only fly a certain distance from their nest to a food source (Zurbuchen et al., 2010). Furthermore, drought from climate change has been found to reduce floral resources for bees (Phillips et al., 2018). Anthropogenic landscape fragmentation and climate change may have
a significant effect on bee populations, bee health, and bee activity. Consequently, the landscape context is critical to understanding the effect of floral resource availability on bee populations.

Traditional field techniques to characterize flowering vegetation traditionally involve manual counts using linear transects or quadrat sampling. However, the wide range of manual sampling methods used by ecologists are often not reported in sufficient detail, leading to a lack of standardized sampling methods (Szigeti et al., 2016). Furthermore, manual methods are often laborious and extremely costly in time and personnel (Szigeti et al., 2016). Due to the time and labor costs associated with manual sampling, many floral samples capture only a fraction of the areas relevant to pollination. In diverse landscapes these limited sampling methods may not adequately capture spatial and temporal variation of floral resources that can be accessed by bees. As a result, local floral communities may be poorly described, leading to weak conclusions on landscape patterns and trends.

Unmanned aerial vehicles (UAVs) can increase the spatial and temporal efficiency of floral sampling as it can quickly capture high resolution imagery of areas covering hundreds of meters. Furthermore, flight paths are highly repeatable over areas of interest which allows users to conduct repeated surveys with minimal spatial variation across flights (Barnas et al., 2019). Drones are frequently being used by ecologists to address questions involving vegetation communities and habitat assessments. Recent advances in sensors and UAV platforms offer opportunities to characterize the dynamic distribution of floral resources at the landscape level, which may provide insight into bee diversity, richness, and abundance.

In the present study, two approaches were used to characterize floral resources in bee pasture: A ground transect survey and machine learning classification analysis of UAV imagery. Additionally, bee diversity surveys were conducted multiple times throughout the flowering season. The research objectives of this study are (1) assess spatial temporal variation of floral resources and bee genera diversity, richness, and abundance and (2) determine if available floral
resources predict the bee genera community at the field sites using simple linear models. I tested two hypotheses. Hypothesis one: I predicted that increased floral diversity would positively correlate with increased bee diversity. My hypothesis is based on previous research that suggests high diversity of resources will support a high diversity of insect consumers (Potts et al., 2003). Hypothesis two: I predicted that increased floral abundance would positively correlate with increased bee abundance. My hypothesis is based on previous research that suggests habitats with abundant flowers have greater possibilities for partitioning of available resources (Potts et al., 2003).

Methods

Study Area

Three field sites were established within the USDA Forest Service Cache National Forest in close proximity to commercial apiaries across the semiarid foothills of Bear River Range in Northern Utah: Blacksmith Fork Canyon Road (BF), Franklin Basin Road (FB), and Twin Creek Road (TC) (Figure 3.1, Table 3.1). This research was part of a larger study to quantify floral resources in non-agricultural areas (Chapter 1). At each field site, a 25 m² plot was established with the corners marked for the duration of the study. Elevation data, precipitation, average maximum temperature, and average minimum temperature at each field site were downloaded from NASA Earth Data (https://app.eears.earthdatacloud.nasa.gov/). See Table 3.2 for weather conditions at the field sites throughout the length of the study.
Figure 3.1

Apiary Field Sites

Note: Apiary field sites located in USDA Forest Service Cache National Forest across the semiarid foothills of Bear River Range in Northern Utah: Blacksmith Fork Canyon Road (BF), Franklin Basin Road (FB), and Twin Creek Road (TC). (Google Earth Pro version 7.3.4.8642).
Table 3.1

Apiary Field Site Latitude and Longitude, Elevation, Slope, and Aspect

<table>
<thead>
<tr>
<th>Field Site</th>
<th>Lat/Lon</th>
<th>Elevation</th>
<th>Slope</th>
<th>Aspect</th>
</tr>
</thead>
<tbody>
<tr>
<td>BF</td>
<td>41°41'14.23&quot;N, 111°27'45.70&quot;W</td>
<td>2,214 m</td>
<td>6.93</td>
<td>310.85</td>
</tr>
<tr>
<td>FB</td>
<td>41°57'8.94&quot;N, 111°35'2.35&quot;W</td>
<td>2,122 m</td>
<td>3.43</td>
<td>128.35</td>
</tr>
<tr>
<td>TC</td>
<td>41°51'50.04&quot;N, 111°34'36.47&quot;W</td>
<td>1,910 m</td>
<td>9.01</td>
<td>153.52</td>
</tr>
</tbody>
</table>


Table 3.2

Weather Events Between Sampling Events at the Field Sites

<table>
<thead>
<tr>
<th>Field Site</th>
<th>Total Precipitation in between sampling events (mm)</th>
<th>Average maximum temperature in between sampling events (C)</th>
<th>Average minimum temperature in between sampling events (C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BF1</td>
<td>32.59</td>
<td>16.95</td>
<td>3.76</td>
</tr>
<tr>
<td>BF2</td>
<td>11.29</td>
<td>25.38</td>
<td>10.52</td>
</tr>
<tr>
<td>BF3</td>
<td>38.61</td>
<td>26.08</td>
<td>12.44</td>
</tr>
<tr>
<td>BF4</td>
<td>47.54</td>
<td>23.04</td>
<td>9.07</td>
</tr>
<tr>
<td>BF1</td>
<td>Total: 130.03</td>
<td>Average: 22.86</td>
<td>Average: 8.95</td>
</tr>
<tr>
<td>FB2</td>
<td>0</td>
<td>24.56</td>
<td>8.99</td>
</tr>
<tr>
<td>FB3</td>
<td>0</td>
<td>28.47</td>
<td>12.01</td>
</tr>
<tr>
<td>FB4</td>
<td>50.06</td>
<td>26.66</td>
<td>12.22</td>
</tr>
<tr>
<td>FB2</td>
<td>Total: 101.46</td>
<td>Average: 25.73</td>
<td>Average: 10.56</td>
</tr>
<tr>
<td>TC1</td>
<td>0</td>
<td>26.47</td>
<td>9.49</td>
</tr>
<tr>
<td>TC2</td>
<td>0</td>
<td>30.003</td>
<td>12.44</td>
</tr>
<tr>
<td>TC3</td>
<td>39.85</td>
<td>28.29</td>
<td>12.92</td>
</tr>
<tr>
<td>TC4</td>
<td>42.64</td>
<td>25.49</td>
<td>9.83</td>
</tr>
<tr>
<td>TC1</td>
<td>Total: 82.49</td>
<td>Average: 27.56</td>
<td>Average: 11.17</td>
</tr>
</tbody>
</table>

**Bee Diversity Survey**

To only include bees foraging on flowers as part of the study, netting sessions were chosen to measure bee diversity at the field sites. A 15 min netting session was completed by four research technicians totaling 1-hour total within the 25 m² plot at each field site. Bees were euthanized with cyanide and then stored in vials along with the flowers they were on at the time of capture. Bees that were not foraging on flowers were not captured. At the end of each netting session, bees would be labeled and stored in refrigerated containers until returning to the Pollinating Insects Research Unit (PIRU) in Logan, Utah. Bee surveys were conducted four times throughout the summer season. Over the course of the study 136 bee samples were collected. Bees were identified to genera using the identification key “The bee genera of North and Central America (Hymenoptera: Apoidea)” written by Michener, McGinley, and Danforth (1994) and using the Discover life bee genera guide (https://www.discoverlife.org/mp/20q?guide=Bee_genera). Specimens were labeled and pinned according to location and time. Once identified, bee samples were deposited into the U.S. National Pollinating Insect Collection at PIRU.

**Ground transect floral vegetation survey**

Three parallel transects were established within the 25 m² plot. Each transect was 25 m long and ~2.75 m wide. Transects were ~4 m apart running parallel to one another. Floral vegetation along each linear transect was sampled four times throughout the season, at each of the three field sites on the same days as the bee surveys. Species and abundance along each linear transect was counted and recorded by an observer. For most flower species, individual flowers were counted. However, for species such as *Achillea millefolium* (Asteraceae) or *Ericameria nauseosa* (Asteraceae) which have extremely small clusters of flowers, inflorescences atop each cyme were counted. “Bottlebrush-like” flowers such as *Agastache urticifolia* (Lamiaceae) were
counted as one inflorescence rather than individual flowers. Vegetation samples were taken of each unique flower species, then labeled and placed in a flower press. Vegetation samples that could not be identified to species were identified to genera. Vegetation samples were catalogued and deposited into the collection at PIRU.

**UAV floral vegetation survey and processing**

UAV remotely sensed images were acquired by a fixed wing, vertical takeoff and landing (VTOL) UAV called the WingtraOne. The WingtraOne UAV was equipped with a 35mm focal length, Sony RX1RII RGB 42MP camera, with a spatial resolution of 7952 x 5304 pixels (Chapter 1). The WingtraOne UAV was flown over each field site 4 times over the Summer around the same time as bee survey and ground transect floral vegetation survey (Chapter 1) (Table 3.3). Acquired data sets were processed using OpenDroneMap (ODM) (OpenDroneMap project (http://opendronemap.github.io/odm/) on the USDA SCINet Atlas (https://scinet.usda.gov/) remote computing cluster (Chapter 1). Each flight area was clipped to 9 acres (3.645 hectares) surrounding the bee diversity survey area using the *gdalUtils* R package (Chapter 1). Anthropogenic objects were clipped out of the image (Chapter 1). 3 RGB, 13 vegetation indices (VIs), and 7 texture covariates were used in the classification models (Chapter 1). A multiple stage machine learning classification was developed using the random forest (RF) algorithm (Chapter 1). This algorithm was used to separate and classify the pixels occupied by flowers, vegetation, and soil/rocks in the imagery (Chapter 1). Floral area for seven unique species were quantified in the classification prediction maps and used as a measure of floral abundance in the images (Chapter 1).
Table 3.3

Sampling Schedule

<table>
<thead>
<tr>
<th></th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
</tr>
</thead>
<tbody>
<tr>
<td>BF flights</td>
<td>6/7/2021</td>
<td>7/15/2021</td>
<td>8/3/2021</td>
<td>8/29/2021</td>
</tr>
<tr>
<td>FB flights</td>
<td>7/1/2021</td>
<td>7/13/2021</td>
<td>8/4/2021</td>
<td>8/27/2021</td>
</tr>
<tr>
<td>FB floral sampling / bee sweep net sampling</td>
<td>6/30/2021</td>
<td>7/13/2021</td>
<td>7/28/2021</td>
<td>8/23/2021</td>
</tr>
<tr>
<td>TC flights</td>
<td>6/29/2021</td>
<td>7/14/2021</td>
<td>8/7/2021</td>
<td>8/24/2021</td>
</tr>
<tr>
<td>TC floral sampling / bee sweep net sampling</td>
<td>7/1/2021</td>
<td>7/14/2021</td>
<td>7/29/2021</td>
<td>8/24/2021</td>
</tr>
</tbody>
</table>

*Note:* Dates of WingtraOne UAV flights, floral vegetation sampling, and bee sweep net sampling across time series. (T) (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek)

*Data Analysis*

Data visualization and statistical tests were performed in the R statistical software version 4.2.0. (R core team, 2022) using the packages *vegan* and *base*. All data were assessed for normality and were transformed if needed before analysis. To complete objective one, the Shannon-Wiener diversity index, rarefaction and abundance were used as a metric to describe bees and flowering vegetation at the field sites. A minimum sample size of 5 and 14 were used in the rarefaction analysis for bees and flowers, respectively. Additionally, Non-metric multidimensional scaling (NMDS) was completed using the function “metaMDS” used to represent the position of bee communities and flower communities in multidimensional space using 20 runs. Stress values were used as a measure of goodness of fit of data points in the NMDS. Stress levels equal zero when data are perfectly represented. Stress levels >0.2 are considered difficult to interpret and considered poor (Boyra et al., 2004; Dexter et al., 2018). Finally, a permutational multivariate analysis of variance (PERMANOVA) was used to determine variance within and between groups of plants and bees across time and field sites.
To complete objective 2, seven simple linear regression models were used to determine the relationship between floral resources and bees present at the field sites. The following pairwise relationships between ground collected flower data and bee data were determined: (1) Ground transect flower Shannon-Wiener diversity index and bee Shannon-Wiener diversity index, (2) ground transect flower rarefaction index and bee rarefaction index, and (3) transformed ground transect flower abundance and bee abundance. A square root transformation was used to normalize ground transect flower abundance data. The following pairwise relationships between UAV collected flower data and bee data were determined: (4) UAV flower abundance and bee Shannon-Wiener diversity index, (5) UAV flower abundance and bee rarefaction index, (6) UAV flower abundance and bee abundance. Finally, (7) the pairwise relationship between the seven UAV flower abundance and the transformed seven ground transect flower species abundance was determined using simple linear regression. A square root transformation was used to normalize the seven ground transect flower species abundance data. Relationships were deemed significant at P values of <0.05.

Results

**UAV floral area**

Seven flower species were successfully classified and quantified using the UAV images for the current study: *Achillea millefolium*, *A. urticifolia*, *E. nauseosa*, *Eriogonum heracleoides* (Polygonaceae), *Geranium viscissimun* (Geraniaceae), *Potentilla glandulosa* (Rosaceae), *Senecio serra* (Asteraceae). Quantified floral area for each flight is shown in Table 3.4. In some time series, low abundance of flowers in the landscape resulted in insufficient training sample numbers for classification. Please see Tabor et al., (2022) (i.e., Chapter 1) for information on model performance and floral classification.
Table 3.4  

Floral Area of Seven Flower Species  

<table>
<thead>
<tr>
<th>Flower species</th>
<th>BF1</th>
<th>BF2</th>
<th>BF3</th>
<th>BF4</th>
<th>FB1</th>
<th>FB2</th>
<th>FB3</th>
<th>FB4</th>
<th>TC1</th>
<th>TC2</th>
<th>TC3</th>
<th>TC4</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Achillea millefolium</em></td>
<td>40.15</td>
<td>NA</td>
<td>193.27</td>
<td>NA</td>
<td>20.06</td>
<td>33.38</td>
<td>83.44</td>
<td>57.46</td>
<td>67.24</td>
<td>66.32</td>
<td>10.75</td>
<td>152.65</td>
</tr>
<tr>
<td>(Asteraceae)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Geranium viscossimum</em></td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>38.24</td>
<td>54.11</td>
<td>NA</td>
<td>NA</td>
<td>111.49</td>
<td>142.38</td>
<td>17.06</td>
<td>NA</td>
</tr>
<tr>
<td>(Geraniaceae)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Potentilla glandulosa</em></td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>15.39</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>7.13</td>
<td>NA</td>
<td>9.34</td>
<td>13.70</td>
</tr>
<tr>
<td>(Rosaceae)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Eriogonum heracleoides</em></td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>271.43</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>3.38</td>
<td>NA</td>
</tr>
<tr>
<td>(Polygonaceae)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Agastache urticifolia</em></td>
<td>214.10</td>
<td>140.18</td>
<td>113.61</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>(Lamiaceae)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Senecio serr</em> (Asteraceae)</td>
<td>73.99</td>
<td>39.78</td>
<td>39.81</td>
<td>NA</td>
<td>NA</td>
<td>8.70</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td><em>Ericameria nauseosa</em></td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>99.41</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>(Asteraceae)</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note:* Floral area of seven flower species using machine learning classification analysis by field site and time series (m²). NA (not applicable) are field sites and time series when flower species was not able to be classified due to low abundance of flowers in the landscape resulting in insufficient training sample numbers (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek).
Ground transect flower surveys

The following 22 flower species were recorded in the transect surveys during the study: 
*Achillea millefolium*, *A. urticifolia*, *Amelanchier alnifolia*, *Aster* sp. (Asteraceae), *Chrysothamnus viscidiflorus* (Asteraceae), *Cirsium* sp. (Asteraceae), *E. nauseosa*, *Cynoglossum officinale* (Boraginaceae), *Erigeron speciosus* (Asteraceae), *Eriogonum* sp. (Polygonaceae), *G. viscossimum*, *Lathyrus latifolius* (Fabaceae), *Linum lewisii* (Linaceae), *Lupinus argenteus* (Fabaceae), *Myosotis* sp. (Boraginaceae), *P. glandulosa*, *Rosa* sp. (Rosaceae), *S. serra*, *Sidalcea oregana* (Malvaceae), *Symphoricarpos oreophilus* (Caprifoliaceae), *Tragopogon* sp. (Asteraceae), and *Triteleia grandiflora* (Asparagaceae) (Table 3.5).

The most abundant inflorescence prevalent during the entire study was *A. urticifolia* and *S. serra*, which was counted 538 and 381 times respectively. Both inflorescences were most frequently found in the Blacksmith Fork field site. *Linum lewisii*, *L. argenteus*, and *Rosa* sp. were the least common flowers across the entire study with only one occurrence each. The Blacksmith Fork field site had the highest abundance of flowers throughout the entire study with 1,292 total inflorescences (Table 3.6). Franklin Basin field site had 515 total inflorescences and Twin Creek field site recorded 293 total inflorescences across the entire study. Across the three field sites, inflorescence counts increased from 541 in time series one, to 648 in time series two and 767 in time series three. Inflorescence counts were lowest in time series four with 144 inflorescences across the three field sites.
# Table 3.5

Total Inflorescences Per Species Using Ground Transect Surveys

<table>
<thead>
<tr>
<th>Flower species</th>
<th>Total transect count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Achillea millefolium (Asteraceae)</td>
<td>348</td>
</tr>
<tr>
<td>Agastache urticifolia (Lamiaceae)</td>
<td>538</td>
</tr>
<tr>
<td>Amelanchier alnifolia (Rosaceae)</td>
<td>20</td>
</tr>
<tr>
<td>Aster sp. (Asteraceae)</td>
<td>55</td>
</tr>
<tr>
<td>Chrysanthemum viscidiflorus (Asteraceae)</td>
<td>60</td>
</tr>
<tr>
<td>Cirsium sp. (Asteraceae)</td>
<td>71</td>
</tr>
<tr>
<td>Cynoglossum officinale (Boraginaceae)</td>
<td>20</td>
</tr>
<tr>
<td>Ericameria nauseosa (Asteraceae)</td>
<td>21</td>
</tr>
<tr>
<td>Erigeron speciosus (Asteraceae)</td>
<td>86</td>
</tr>
<tr>
<td>Eriogonum sp. (Polygonaceae)</td>
<td>4</td>
</tr>
<tr>
<td>Geranium viscosissimum (Geraniaceae)</td>
<td>280</td>
</tr>
<tr>
<td>Lathyrus latifolius (Fabaceae)</td>
<td>8</td>
</tr>
<tr>
<td>Linum lewisii (Linaceae)</td>
<td>1</td>
</tr>
<tr>
<td>Lupinus argenteus (Fabaceae)</td>
<td>1</td>
</tr>
<tr>
<td>Myosotis sp. (Boraginaceae)</td>
<td>145</td>
</tr>
<tr>
<td>Potentilla glandulosa (Rosaceae)</td>
<td>7</td>
</tr>
<tr>
<td>Rosa sp. (Rosaceae)</td>
<td>1</td>
</tr>
<tr>
<td>Senecio serra (Asteraceae)</td>
<td>381</td>
</tr>
<tr>
<td>Sidalcea oregana (Malvaceae)</td>
<td>21</td>
</tr>
<tr>
<td>Symphoricarpus oreophilus (Caprifoliaceae)</td>
<td>25</td>
</tr>
<tr>
<td>Tragopogon sp. (Asteraceae)</td>
<td>2</td>
</tr>
<tr>
<td>Triteleia grandiflora (Asparagaceae)</td>
<td>5</td>
</tr>
</tbody>
</table>

*Note:* Species that were not able to be identified to species were identified to genera.
Table 3.6

*Average Floral Resource and Bee Genera Diversity, Richness, and Abundance Across Field Sites and Time Series*

<table>
<thead>
<tr>
<th></th>
<th>Bees</th>
<th>Floral Resources</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Shannon-Wiener diversity</td>
<td>Rarefaction by site</td>
<td>Abundance by site</td>
<td>Shannon-Wiener diversity</td>
<td>Rarefaction by site</td>
<td>Abundance by site</td>
</tr>
<tr>
<td></td>
<td>index by site</td>
<td></td>
<td></td>
<td>index by site</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BF</td>
<td>0.91</td>
<td>2.35</td>
<td>70</td>
<td>0.93</td>
<td>2.98</td>
<td>1292</td>
</tr>
<tr>
<td>FB</td>
<td>0.65</td>
<td>2.05</td>
<td>38</td>
<td>0.57</td>
<td>2.31</td>
<td>515</td>
</tr>
<tr>
<td>TC</td>
<td>0.67</td>
<td>2.04</td>
<td>28</td>
<td>0.33</td>
<td>1.72</td>
<td>293</td>
</tr>
<tr>
<td></td>
<td>Shannon-Wiener diversity</td>
<td>Rarefaction by time series</td>
<td>Abundance by time series</td>
<td>Shannon-Wiener diversity</td>
<td>Rarefaction by time series</td>
<td>Abundance by time series</td>
</tr>
<tr>
<td></td>
<td>index by time series</td>
<td></td>
<td></td>
<td>index by time series</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T1</td>
<td>1.08</td>
<td>2.63</td>
<td>41</td>
<td>0.9449</td>
<td>3.24</td>
<td>541</td>
</tr>
<tr>
<td>T2</td>
<td>1.03</td>
<td>2.6</td>
<td>38</td>
<td>0.6942</td>
<td>2.6</td>
<td>648</td>
</tr>
<tr>
<td>T3</td>
<td>0.61</td>
<td>1.87</td>
<td>39</td>
<td>0.5877</td>
<td>2.18</td>
<td>767</td>
</tr>
<tr>
<td>T4</td>
<td>0.27</td>
<td>1.48</td>
<td>18</td>
<td>0.2084</td>
<td>1.33</td>
<td>144</td>
</tr>
</tbody>
</table>

Note: (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek, T = Time series).
Note: A minimum sample size of 14 was used for the rarefaction analysis. FB1 had the highest rarified species richness of 3.88, while FB4, TC3, and TC4 all had the lowest rarified floral species richness of one (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek).
Blacksmith Fork had the highest average Shannon-Wiener diversity index for floral species with 0.92, followed by Franklin Basin with 0.57 and Twin Creek with 0.33 across the entire study (Table 3.6). Across all field sites, the average Shannon-Wiener diversity index for floral species was highest in time series one with 0.94 and gradually fell to eventually 0.21 in time series four. Blacksmith Fork had the highest average rarified species richness for floral species with 2.98, followed by Franklin Basin with 2.30 and Twin Creek with 1.72 across the study (Table 3.6, Figure 3.2). Across all field sites, the average rarified species richness for floral species was highest in time series one with 3.24. In time series two it fell to 2.6, then 2.18 in time series three and finally 1.33 in time series four. Franklin Basin time series one had the highest rarified species richness sampling event in the study with 3.88 while Franklin Basin time series four, Twin Creek time series three, and Twin Creek time series four had the lowest rarified species richness of one (Figure 2.2).

NMDS stress metric produced an acceptable score of 0.03. Analysis of the Euclidean distance in ordination space between field sites observed across the entire length of study revealed that floral species were similar between the Blacksmith Fork and Franklin Basin field sites due to the highly overlapping convex hulls (Figure 3.3). Conversely, the floral species present at Twin Creek field site was very different than the other two sites and mostly consisted of *G. viscossimum*, *Eriogonum sp.*, and *P. glandulosa* (Figure 3.3). Analysis of the Euclidean distance in ordination space between time series observed across all three study sites revealed that floral species were similar across time series one through three based on the highly overlapping convex hulls. Conversely, the floral species present at time series four was very different than the prior time series because of the high prevalence of *G. viscossimum* and *E. heracleoides*.

Permutational multivariate analysis of variance (PERMANOVA) suggested significant variance of floral resources across the sites ($R^2 = 0.29, P = 0.001$). However, PERMANOVA suggested no significant differences of floral resources across time ($R^2 = 0.12, P = 0.09$).
Figure 3.3

NMDS Plot of Ground Transect Floral Resources Grouped by Field Site (Top) and Time Series (Bottom)

Notes: Plots show variance of floral resources at Twin Creek site and variance of floral resources in time series four (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek).
Table 3.7

Total Bee Genera Recorded Across All Sites and Time Series

<table>
<thead>
<tr>
<th>Genera</th>
<th>Diet</th>
<th>Total count</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Andrena</em> (Andrenidae)</td>
<td>Generalists and specialists</td>
<td>3</td>
</tr>
<tr>
<td><em>Apis</em> (Apidae)</td>
<td>Generalists</td>
<td>54</td>
</tr>
<tr>
<td><em>Bombus</em> (Apidae)</td>
<td>Generalists</td>
<td>16</td>
</tr>
<tr>
<td><em>Ceratina</em> (Apidae)</td>
<td>Mostly generalists</td>
<td>1</td>
</tr>
<tr>
<td><em>Diadasia</em> (Apidae)</td>
<td>Specialists</td>
<td>10</td>
</tr>
<tr>
<td><em>Halictus</em> (Halictidae)</td>
<td>Generalists</td>
<td>15</td>
</tr>
<tr>
<td><em>Hoplitis</em> (Megachilidae)</td>
<td>Generalists and specialists</td>
<td>4</td>
</tr>
<tr>
<td><em>Hylaeus</em> (Colletidae)</td>
<td>Generalists</td>
<td>5</td>
</tr>
<tr>
<td><em>Lasioglossum</em> (Halictidae)</td>
<td>Mostly generalists</td>
<td>11</td>
</tr>
<tr>
<td><em>Megachile</em> (Megachilidae)</td>
<td>Mostly generalists</td>
<td>7</td>
</tr>
<tr>
<td><em>Osmia</em> (Megachilidae)</td>
<td>Mostly generalists</td>
<td>10</td>
</tr>
</tbody>
</table>

Bee Surveys

136 bees from the following 11 genera were recorded in the bee net surveys during the study: *Andrena* (Andrenidae), *Apis* (Apidae), *Bombus* (Apidae), *Ceratina* (Apidae), *Diadasia* (Apidae), *Halictus* (Halictidae), *Hoplitis* (Megachilidae), *Hylaeus* (Colletidae), *Lasioglossum* (Halictidae), *Megachile* (Megachilidae), and *Osmia* (Megachilidae) (Table 3.7). The most abundant bee genera collected on flowers during the study was *Apis* and *Bombus*, which was counted 54 and 16 times respectively across the entire study. *Ceratina*, and *Andrena* were the least common bee genera collected on flowers across the study with one and three occurrences respectively. The Blacksmith Fork field site had the highest abundance of bees throughout the entire study with 70 individual bees collected on flowers (Table 3.6). Franklin Basin field site had 38 individual bees and Twin Creek field site recorded 28 individual bees collected on flowers across the entire study. During the entire study, across the three field sites, bee abundance was highest in time series one with 41 individual bees and lowest in time series four with 18 individual bees.
Blacksmith Fork had the highest average Shannon-Wiener diversity index for bee genera with 0.91, followed by Twin Creek with 0.66 and Franklin Basin with 0.65 across the entire study (Table 3.6). Throughout the entire study across all field sites, the average Shannon-Wiener diversity index for bee genera was highest in time series one with 1.08 and fell to 0.27 in time series four. Blacksmith Fork had the highest average rarified bee genera richness with 2.35, followed by Franklin Basin with 2.05 and Twin Creek with 2.04 across the entire study (Table 3.6, Figure 3.4). Throughout the study across all field sites, the average rarified bee genera richness was highest in time series one with 2.63 and fell to 1.48 in time series four. Rarified bee genera richness was highest at Twin Creek time series one sampling event with 2.9, and the lowest at Franklin Basin time series three and Twin Creek time series four with one (Figure 3.4).

Some bees were found foraging on flower species that were quantified using the UAV imagery. *Apis* and *Osmia* genera were found foraging on *A. millefolium*. *Apis*, *Bombus*, *Megachile*, and *Osmia* genera were found foraging on *A. urticifolia*. The *Bombus* genus were found foraging on *E. nauseosa*. The *Apis* genus was found foraging on *E. heracleoides*. *Andrena*, *Ceratina*, *Diadasia*, *Halictus*, *Hylaeus*, and *Megachile* genera were found foraging on *G. viscossimum*. *Andrena*, *Bombus*, *Hoptilis*, *Hylaeus*, and *Megachile* were found foraging on *P. glandulosa*.

NMDS stress metric produced an acceptable score of 0.07. Analysis of the Euclidean distance in ordination space between field sites and time series observed across the entire length of study revealed that bee genera was similar due to the overlapping convex hulls (Figure 3.5). Permutational multivariate analysis of variance (PERMANOVA) suggested significant variance of bee genera across time series ($R^2 = 0.18$, $P = 0.04$). However, PERMANOVA suggested no significant differences of bee genera across field sites ($R^2 = 0.16$, $P = 0.67$).
Figure 3.4

Rarefaction Plot of Bee Genera Richness for Each Sampling Event

Note: A minimum sample size of five was used for the rarefaction analysis. Rarified bee genera richness was highest at TC1 sampling event with 2.9, and the lowest rarified bee genera richness at FB3 and TC4 with one (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek).
Figure 3.5

NMDS Plot of Bee Genera Grouped by Field Site (Top) and Time Series (Bottom)

Note: Plots shows bee genera was similar across field sites and time series (BF = Blacksmith Fork, FB = Franklin Basin, TC = Twin Creek).
Simple linear models

Five of seven pairwise simple linear models were significant (Table 3.8, Figure 3.6). (1) There was a positive and significant relationship between ground transect flower Shannon-Wiener diversity index and bee Shannon-Wiener diversity index ($R^2 = 0.31$, $F = 6.02$, $Df = 10$, beta coefficient = 0.64, $P = 0.03$). (2) There was a positive and significant relationship between ground transect flower rarefaction index and bee rarefaction index ($R^2 = 0.31$, $F = 5.9$, $Df = 10$, beta coefficient = 0.41, $P = 0.04$). (3) There was a positive and significant relationship between transformed ground transect flower abundance and bee abundance ($R^2 = 0.76$, $F = 35.93$, $Df = 10$, beta coefficient = 1.26, $P = 0.0001$). (4) There was a positive but insignificant relationship between UAV flower abundance and Bee Shannon-Wiener diversity index ($R^2 = 0.16$, $F = 3.16$, $Df = 10$, beta coefficient = 0.002, $P = 0.11$). (5) There was a positive but insignificant relationship between UAV flower abundance and Bee rarefaction index ($R^2 = 0.11$, $F = 2.41$, $Df = 10$, beta coefficient = 0.002, $P = 0.15$). (6) There was a positive and significant relationship between UAV flower abundance and Bee abundance ($R^2 = 0.35$, $F = 6.86$, $Df = 10$, beta coefficient = 0.05, $P = 0.03$). (7) There was a positive and significant relationship between UAV flower abundance and the transformed seven ground transect flower species abundance ($R^2 = 0.20$, $F = 5.12$, $Df = 15$, beta coefficient = 0.05, $P = 0.04$)
### Table 3.8

**Results of Seven Pairwise Simple Linear Regression Models**

<table>
<thead>
<tr>
<th>Predictor variable</th>
<th>Response variable</th>
<th>P-value</th>
<th>t-value</th>
<th>Std. error</th>
<th>Beta correlation coefficient estimate (slope)</th>
<th>Residual standard error</th>
<th>Df</th>
<th>Adjusted R-squared</th>
<th>F-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground transect Flower Shannon-Wiener diversity index</td>
<td>Bee Shannon-Wiener diversity index</td>
<td>0.03*</td>
<td>2.45</td>
<td>0.26</td>
<td>0.64</td>
<td>0.38</td>
<td>10</td>
<td>0.31</td>
<td>6.02</td>
</tr>
<tr>
<td>Ground transect Flower rarefaction index</td>
<td>Bee rarefaction index</td>
<td>0.04*</td>
<td>2.43</td>
<td>0.17</td>
<td>0.41</td>
<td>0.56</td>
<td>10</td>
<td>0.31</td>
<td>5.9</td>
</tr>
<tr>
<td>Ground transect Flower abundance (transformed)</td>
<td>Bee abundance</td>
<td>0.0001*</td>
<td>5.99</td>
<td>0.21</td>
<td>1.26</td>
<td>4.55</td>
<td>10</td>
<td>0.76</td>
<td>35.93</td>
</tr>
<tr>
<td>UAV flower abundance</td>
<td>Bee Shannon-Wiener diversity index</td>
<td>0.11</td>
<td>1.78</td>
<td>0.001</td>
<td>0.002</td>
<td>0.42</td>
<td>10</td>
<td>0.16</td>
<td>3.16</td>
</tr>
<tr>
<td>UAV flower abundance</td>
<td>Bee rarefaction index</td>
<td>0.15</td>
<td>1.55</td>
<td>0.001</td>
<td>0.002</td>
<td>0.63</td>
<td>10</td>
<td>0.11</td>
<td>2.41</td>
</tr>
<tr>
<td>UAV flower abundance</td>
<td>Bee abundance</td>
<td>0.03*</td>
<td>2.61</td>
<td>0.02</td>
<td>0.05</td>
<td>7.52</td>
<td>10</td>
<td>0.35</td>
<td>6.86</td>
</tr>
<tr>
<td>UAV flower abundance</td>
<td>Ground transect flower abundance (seven species) (transformed)</td>
<td>0.04*</td>
<td>2.26</td>
<td>0.02</td>
<td>0.05</td>
<td>4.28</td>
<td>15</td>
<td>0.20</td>
<td>5.12</td>
</tr>
</tbody>
</table>

*Note: Simple linear regression models used to determine the relationship between floral resources and bees present at the field sites. Square root transformations were used to normalize ground transect flower abundance and ground transect flower abundance (seven species).*

* Represents a significant p-value.
Figure 3.6

*Plot Results of Seven Pairwise Simple Linear Regression Models*

*Note:* Models used to determine the relationship between floral resources and bees present at the field sites. Square root transformations normalized ground transect flower abundance and ground transect flower abundance (seven species).
Discussion

Spatial and temporal variability of floral resources and bee genera

The results of the PERMANOVA analysis suggest variance of flowers across sites. The NMDS plot supports this inference due to the dissimilarity of flower species at the Twin Creek field site because of the abundance of *G. viscossimum*, *Eriogonum* sp., and *P. glandulosa*. A pattern emerges in the floral NMDS plot through time because of the dissimilarity of floral resources in time series four. This may be from the extremely dry conditions at the end of the summer, causing *G. viscossimum* and *E. heracleoides* to be the most prevalent floral resource. The bee genera were the same across sites suggested by the NMDS. The bee genera however did vary through time, suggested by the PERMANOVA analysis. The NMDS plot is mostly similar in bee genera across time. However, a pattern emerges suggesting that *Bombus*, *Halictus*, *Hoptilis*, and *Osmia* were most prevalent in time series two.

The Blacksmith fork field site had the highest diversity, richness, and abundance of both flowers and bees. This may be due to the largest amount of precipitation at that field site with 130 mm throughout the study (Table 3.2). Furthermore, the Blacksmith Fork field site has the highest elevation of the field sites with 2,214 meters, and the lowest temperatures throughout the season. Blacksmith Fork field site is also the only field site located on a north facing slope which may enable this site to maintain its water more efficiently. Overall diversity and richness decreased through time for both flowers and bees. Abundance of flowers increased from time series one to time series three and then significantly decreased in time series four.

Floral resources predict bee genera community

To characterize floral resources, I used ground transect surveys and machine learning classifications of UAV imagery. Additionally, I determined the relationship between the available floral resources and bee community structure. I hypothesized that increased floral diversity would
positively correlate with increased bee diversity. I also hypothesized that increased floral abundance would positively correlate with increased bee abundance. The ground transect data supports my two hypotheses. Bee genera diversity and abundance, as revealed by linear regression, was predicted by floral resource diversity and abundance. Furthermore, bee genera richness was also dependent on floral resource richness collected from ground transects, as revealed by linear regression. Additionally, the UAV imagery classification supports my second hypothesis, that increased floral abundance would positively correlate with increased bee abundance. The abundance of bees at the field sites, as revealed by linear regression, was dependent on floral resource abundance. I also found a significant correlation between the classified floral abundance and the abundance of the same seven species found along the ground transects. Of all the pairwise linear models, I found that bee diversity was best predicted by on flower diversity (using ground transect data) at the field sites. While five of the seven pairwise simple linear models were significant, the strength of the linear relationship was weak, suggested by the low $R^2$ values. Given the sample size of 12, increased sample size will likely yield stronger patterns between floral resources and bee community diversity and richness.

The ground transect survey revealed twenty-two unique flower species. Seven flower species or about 32% of the overall species were successfully classified in the UAV imagery. The validity of the classifications are supported by the sensitivity and specificity values produced by the random forest (Chapter 1) and by the significant correlation found between floral abundance in the classification models and floral abundance of the same seven species in ground transect data using the simple linear model. Considering only 32% of the overall flower species were classified, not enough species were represented in the classification models, thus only UAV floral abundance was used as a predictor variable in the simple linear models. However, the models were successful in predicting bee abundance given the lack of data. This suggests that the seven classified flower species may be indicators for healthy bee habitat, a healthy floral resource
community, or water availability. This is also interesting because *A. millefolium* was the most prevalent flower in the study, and has been suggested to attract very few bees. By including this species, the simple linear regression model was able to predict bee abundance. This suggests that flowers that are more attractive to bees may accompany *A. millefolium* on the landscape, which may be a reason the models found a significant relationship.

The variation in phenology and structure of floral species adds to the variability of the terrain in non-agricultural settings, and this increases the challenge of quantifying the flower by UAV based imagery. Plants have high structural variation because they can develop flowers along its branches at different heights and overlap each other. For example, dense groups of *S. serra* have a high number of flowers overlapping each other several times as opposed to bushes that are sparse and not overlapping such as *A. millefolium*. This high level of variation was likely the main factor that contributed to the weak, but significant, relationship found between the numbers of flowers measured along the ground transect and those estimated using the UAV imagery. Classifications would benefit from a more robust and comprehensive UAV sampling plan, to better characterize the variability of floral resources in UAV imagery through increased sample sizes across a variety of habitats, floral phenology, and light variation. To address what is detected by the UAV, I suggest using a commercial grade GPS to establish transect locations for more accurate comparison between ground transect and UAV imagery. Furthermore, the volume of these flowers should also be considered by establishing equations relating to the volume of the above ground biomass.

**Limitations**

UAV imagery is dependent on the environmental conditions at the time of data collection. UAV flights were scheduled around bee / transect surveys, resulting in inadequate weather conditions i.e., heavy clouds, precipitation, and smoke which sometimes prevented UAV
data collection. While most UAV flights were within a week of bee / transect surveys, one flight, Blacksmith Fork time series two was conducted over two weeks after bee / transect surveys. However, the flowers that were classified: *A. urticifolia* and *S. serra* have long seasons of bloom and were believed to have similar inflorescence numbers at the time of UAV flight as at the time of the bee and transect surveys.

This research was one of the first attempts to quantify the number of multiple flower species in non-agricultural landscapes using UAVs. Classification models require significant amounts of training data to create a robust model that captures all the variation within a flower species. Thus, the flowers that were classified were also the most abundant flowers recorded along the ground transect. Rare flowers did not provide adequate floral abundance for a classification model to be built. Additionally, the size of inflorescences is also a limiting factor for detection. Inflorescences ~1 cm or smaller were unable to be classified because of the spatial resolution of the RGB sensor.

**Significance**

The floral resources in the environment (i.e. pollen and nectar) are needed to support the reproduction and health of managed and wild bees. Research has found that bees provided with natural forage instead of protein supplements had less pathogens and parasites, and were healthier (DeGrandi-Hoffman et al., 2016). As suitable bee pasture becomes more uncommon, beekeepers are increasingly pasturing their hives on U.S. public lands managed by U.S. Forest Service, U.S. Fish and Wildlife service, and Bureau of Land Management, in search for good bee pasture (Wojcik et al., 2018). As a non-native species to North America, there are unanswered questions about how the introduction of honey bees into these areas may affect native bee species, and vice-versa (Henry & Rodet, 2018). Recent declines in native bee populations fuel concerns that pasturing managed honey bees in natural areas may limit resources for native bees. Beekeepers
are dependent on environmental conditions that drive many to move their colonies from one area to another in search of better nectar and pollen resources. This may lead to concentrations of apiaries in limited areas, regardless of population density and the carrying capacity of the landscape (Durant, 2019; Henry & Rodet, 2018). Additionally, some beekeepers concentrate on only some areas in search of a few particular species of plants that provide the most desired honey types (Al-Ghamdi et al., 2016). Overstocking of colonies may lead to overgrazing of floral resources by apiaries, negatively impacting both managed honey bees and native bee species.

Regarding U.S. public land, no directive exists to determine the number of honey bee colonies to be placed per unit area, nor is there an established minimum distance between two adjacent apiaries to minimize competition caused by the overlapping of foraging ranges and subsequent decline of productivity of colonies (Al-Ghamdi et al., 2016). The methods of this study may be helpful in determining apiary locations by establishing distance thresholds and density thresholds based on the available floral resources in the environment.
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CHAPTER FOUR
Summary and Conclusions

In this thesis, I examined the relationship between the floral community composition and the bee community composition at three field sites. UAV surveys with machine learning classification analysis and ground transect surveys were used to characterize the spatiotemporal variation of floral resources at three unique field sites. Based on the dynamic changes of floral area classified in UAV images, it was determined that UAVs offer an efficient method of capturing flowering and changes of flower coverage for different species. However, only seven out of twenty-two total species were classified using the UAV imagery due to spatial resolution of UAV imagery limitations, and low flower abundance which prevented me from developing appropriate amounts of training data. Simple linear regression models support my hypothesis that the floral resource data collected from ground transect surveys predicts bee diversity, bee richness, and bee abundance. I found floral abundance data captured by UAV predicts bee abundance at the field sites. I also found UAV floral abundance predicts ground transect floral abundance suggesting a positive relationship between different sampling methods. My results support previous research that suggests a high diversity of resources will support a high diversity of insect consumers, and habitats with abundant flowers have greater possibilities for partitioning of available resources. My results demonstrate that UAVs are a feasible and efficient method for characterizing floral resources in non-agricultural settings. Classification models would benefit from a more robust and comprehensive UAV sampling plan, to better characterize the variability of floral resources in UAV imagery through increased sample sizes across a variety of habitats, floral phenology, and light variation.

This research was one of the first attempts to quantify multiple flower species using UAV technology in non-agricultural environments, where topography, vegetation, and flower
inflorescence size are variable. The models developed in this study demonstrate a robust framework to measure abundance of flowering vegetation via UAV RGB aerial imagery. Overall, UAV based RGB images are promising for field phenotypic and phenological research in non-agricultural areas.

My results bring more insights into the relationship between the floral community composition and bee community composition. The methods developed in my research may support apiarists and land managers to make informed decisions in managing wild and domesticated bee species. Furthermore, these methods may aid in determining appropriate apiary locations in U.S. public lands, and establishing distance thresholds between apiaries and density thresholds within apiaries based on the available floral resources and the associated bee community in the landscape.
APPENDICES
Appendix A

Figure A.1

Blacksmith Fork Time Series One Land Cover Classification MDA Plot

![Figure A.1: Blacksmith Fork Time Series One Land Cover Classification MDA Plot](image1)

Figure A.2

Blacksmith Fork Time Series One Land Cover Classification Reduced Covariates MDA Plot

![Figure A.2: Blacksmith Fork Time Series One Land Cover Classification Reduced Covariates MDA Plot](image2)
Figure A.3

Blacksmith Fork Time Series One Flower Classification MDA Plot

Figure A.4

Blacksmith Fork Time Series One Flower Classification Reduced Covariates MDA Plot
Figure A.5

Blacksmith Fork Time Series Two Land Cover Classification MDA Plot

Figure A.6

Blacksmith Fork Time Series Two Land Cover Classification Reduced Covariates MDA Plot
Figure A.7

*Blacksmith Fork Time Series Two Flower Classification MDA Plot*

![Figure A.7 Diagram]

Figure A.8

*Blacksmith Fork Time Series Two Flower Classification Reduced Covariates MDA Plot*

![Figure A.8 Diagram]
Figure A.9

Blacksmith Fork Time Series Three Land Cover Classification MDA Plot

Figure A.10

Blacksmith Fork Time Series Three Land Cover Classification Reduced Covariates MDA Plot
Figure A.11

*Blacksmith Fork Time Series Three Flower Classification MDA Plot*

![flowerv_rf_full](image)

Figure A.12

*Blacksmith Fork Time Series Three Flower Classification Reduced Covariates MDA Plot*

![flowerv_rf](image)
Figure A.13

Blacksmith Fork Time Series Four Land Cover Classification MDA Plot

Figure A.14

Blacksmith Fork Time Series Four Land Cover Classification Reduced Covariates MDA Plot
Figure A.15

*Franklin Basin Time Series One Land Cover Classification MDA Plot*

Figure A.16

*Franklin Basin Time Series One Land Cover Classification Reduced Covariates MDA Plot*
Figure A.17

*Franklin Basin Time Series One Flower Classification MDA Plot*

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flower_rf_full
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Figure A.18

*Franklin Basin Time Series One Flower Classification Reduced Covariates MDA Plot*

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flower_rf
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Figure A.19

Franklin Basin Time Series Two Land Cover Classification MDA Plot

![Figure A.19 Diagram](image)

Figure A.20

Franklin Basin Time Series Two Land Cover Classification Reduced Covariates MDA Plot

![Figure A.20 Diagram](image)
Figure A.21

Franklin Basin Time Series Two Flower Classification MDA Plot

Figure A.22

Franklin Basin Time Series Two Flower Classification Reduced Covariates MDA Plot
Figure A.23

*Franklin Basin Time Series Three Land Cover Classification MDA Plot*

![Diagram showing mean decrease in accuracy and gini for various covariates.](image1)

Figure A.24

*Franklin Basin Time Series Three Land Cover Classification Reduced Covariates MDA Plot*

![Diagram showing mean decrease in accuracy and gini for various reduced covariates.](image2)
Figure A.25

*Franklin Basin Time Series Four Land Cover Classification MDA Plot*

Figure A.26

*Franklin Basin Time Series Four Land Cover Classification Reduced Covariates MDA Plot*
Figure A.27

*Twin Creek Time Series One Land Cover Classification MDA Plot*

![MDA Plot for Twin Creek Time Series One Land Cover Classification](image1)

Figure A.28

*Twin Creek Time Series One Land Cover Classification Reduced Covariates MDA Plot*

![MDA Plot for Twin Creek Time Series One Land Cover Classification Reduced Covariates](image2)
Figure A.29

*Twin Creek Time Series One Flower Classification MDA Plot*

Figure A.30

*Twin Creek Time Series One Flower Classification Reduced Covariates MDA Plot*
Figure A.31

*Twin Creek Time Series Two Land Cover Classification MDA Plot*

![Figure A.31](image)

Figure A.32

*Twin Creek Time Series Two Land Cover Classification Reduced Covariates MDA Plot*

![Figure A.32](image)
Figure A.33

Twin Creek Time Series Two Flower Classification MDA Plot

Figure A.34

Twin Creek Time Series Two Flower Classification Reduced Covariates MDA Plot
Figure A.35

*Twin Creek Time Series Three Land Cover Classification MDA Plot*

![Diagram for Figure A.35]

Figure A.36

*Twin Creek Time Series Three Land Cover Classification Reduced Covariates MDA Plot*

![Diagram for Figure A.36]
Figure A.37

Twin Creek Time Series Three Flower Classification MDA Plot

Figure A.38

Twin Creek Time Series Three Flower Classification Reduced Covariates MDA Plot
Figure A.39

*Twin Creek Time Series Four Land Cover Classification MDA Plot*

![Twin Creek Time Series Four Land Cover Classification MDA Plot](image)

Figure A.40

*Twin Creek Time Series Four Land Cover Classification Reduced Covariates MDA Plot*

![Twin Creek Time Series Four Land Cover Classification Reduced Covariates MDA Plot](image)
Figure A.41

*Twin Creek Time Series Four Flower Classification MDA Plot*

![Diagram showing MDA plot for Twin Creek Time Series Four Flower Classification]

Figure A.42

*Twin Creek Time Series Four Flower Classification Reduced Covariates MDA Plot*

![Diagram showing MDA plot for Twin Creek Time Series Four Flower Classification Reduced Covariates]