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A Drone's View of Plant Disease Ecology and Ethics



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**A DRONE'S VIEW OF PLANT DISEASE ECOLOGY AND ETHICS**

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by

**Jon R. Detka**

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**Abstract**

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by

Jon R. Detka

As a drone pilot, ecologist, and scientist comfortable with emerging remote sensing technologies I have designed my dissertation around using drones to understand landscape processes and the ethical challenges associated with using drones as they intersect with privacy concerns. This work is organized into two main parts, with the first part exploring the role of plant pathogens in wildlands and the use of drones to enhance plant disease research. The second part examines the legal and ethical implications of commercial use of drone technology.

In the first half, I used drones to map the distribution of host plants in diverse wildland communities, contributing to a better understanding of plant diseases in two closely related wildland manzanita plant species. I employed advanced computer modeling techniques to accurately identify dominant plant species, crucial for conservation efforts in this challenging landscape. Additionally, I used analytical approaches to examine the relationship between the amount of time that leaves have wet surfaces and the association with the spatial distribution of plants along a coastal to inland climate gradient, providing valuable insights into disease dynamics.

The second part of this work explores the ethical considerations of using drones and the importance of balancing the benefits of drone technology with minimizing harm to the environment, respecting privacy expectations, and ensuring transparency and equity. I analyzed the historical, legal, and policy aspects of drone use, focusing on federal safety regulations and state privacy laws. The tension between federal and state regulations underscores the need for drone pilots to be well-versed in both. Then, I examine the existing federal certification framework

for drone pilots and identify the lack of training on privacy ethics and best practices for maintaining transparency. I propose expanding professional certification beyond the federal program to include a focus on privacy concerns. This certification, administered through non-profit organizations collaborating with commercial and higher-education entities, can help establish industry standards and provide essential training for drone pilots.

Overall, this dissertation demonstrates the significant potential of drones in ecological research, particularly in studying plant diseases and wildland conservation. And, highlights the importance of ethical considerations, privacy protection, and transparent practices in the use of drone technology for scientific purposes.

To my loving wife, Erin. Your encouragement has supported me, your strength has inspired me, and your love has sustained me through every chapter of this academic endeavor.

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# Chapter 1

# Introduction

This dissertation focuses on the current application and ethical uses associated with a rapidly emerging technology - remotely piloted aircraft - or drones. This research has now grown to encompass both contemporary applications in ecology and challenges around the ethics of privacy associated with using drone technologies for remote sensing. This work is rooted in some of my earliest academic experiences in higher education. As an undergraduate majoring in Earth Systems Science & Policy at California State University Monterey Bay in the late-1990's, I was keenly aware of the intersections between systems thinking, the natural and physical sciences, and environmental policy. At the time, I found that my strengths were in utilizing emerging computing technologies, responding to technical problem-solving, and in my affinity for supporting others through teaching in the natural, physical, and computing sciences. I found that I was impatient with prolonged policy design and decision-making, but thrived in more dynamic, fast-paced settings that led to direct actionable change. However, I understood the importance of the policy decision-making processes, deliberately engaged in policy conversation, and worked to demonstrate my understanding - primarily in an apolitical fashion. My affect towards policy shifted dramatically as I began to learn about remote sensing technologies, especially emerging global positioning systems (GPS) technologies. At the time, GPS technology began to see more widespread use outside of strictly military applications, and a number of ethical concerns arose out of governmental decisions to restrict availability and accuracy. Among these issues were concerns about privacy and equity. I found myself engaging more deeply in remote sensing policy conversations with a stronger commitment to thinking about the broader societal implications associated with mapping technologies.

Coming to UCSC as an environmental studies PhD student rekindled this interest in the applications and ethical challenges associated with privacy rights and remote sensing technology. Although, the ethical component came much later. I was at the pinnacle moment in my PhD experience developing my dissertation research prospectus when the COVID-19 pandemic sent us all home, curtailing many of our opportunities for communication and collaboration. I was faced with the likely challenge of implementing a landscape-level wildland plant disease ecology project alone in often inaccessible terrain with concerns for my impact on the sensitive plant community I was studying. I had designed my ecological research using ground-based mapping, conventional transect survey methods and micrometeorology technology that I was well acquainted with. The social science component of my work, which was initially designed around citizen science-based ecology learning experiences with K-12 students, had to be put on hold with no clear indication of when 'normal' learning experiences would resume.

Faced with my ground-based ecological research challenges, I returned to my interests in remote sensing and geographic information systems (GIS) analytical approaches. Freely available satellite imagery was insufficient to address the species-level questions that I was interested in, and high-resolution satellite imagery was financially out of reach. Artificial intelligence and machine learning approaches in spatial analytics were rapidly developing and drone aircraft were increasingly available, although largely cost-prohibitive. I responded in my usual improvisational fashion and designed a drone-on-a-stick solution, rigging an inexpensive GoPro to a pool-sweep boom with a skateboard bearing swivel, and bluetooth iPad connection. I had developed an affordable high-resolution remote sensing system that, in spite of its limitations, got things moving (although very slowly and at a very limited scale). Then, a turning point happened when researchers and educators from UCANR and University California Natural Reserve System and University California Agricultural and Natural Resources who were scouting flight training locations for a pending DroneCamp experience found me, quite literally in the bushes. I was laboriously moving along with my drone-on-a-stick and heard - "Someone needs to get him a drone". Soon after, I found myself with access to professional drone technology courtesy of the UC system and part of a supportive community of devoted technology educators, drone researchers, artists, and policy-makers committed to my learning and drone-based research success.

It did not take long to realize the potential of drone remote sensing technology as a tool for supporting ecological conservation, as well as the potential privacy issues associated with operating in proximity to spaces where individuals have reasonable expectations of privacy. I saw this as an opportunity to evaluate my own positionality and dove deeply into issues of technology access and systemic racism. I worked to consider scenarios through ethical lenses and began to consider the impacts of my actions as a pilot and how I might explore these issues with students in the classroom. The second half of my dissertation is my response to the identification of a need to balance the beneficial applications of drone technology with practices and processes for evaluating their safe and responsible use. And, it outlines an approach to how non-profit organizations and institutions of higher education can support drone pilots with training on safe operations and best-practices for respecting privacy, safeguarding security, and maintaining transparency in flight operations.

In the first half of this work, I utilized drones and computer modeling to map host plants in wildland communities, enhancing our understanding of diseases in two manzanita species and their relationship with climate conditions and plant distribution along a coastal-inland gradient.

Wildland plant disease outbreaks are important consequences of global climate change and present complex challenges for wildland conservationists (Laine, 2023). Wildlands are vulnerable to various interacting ecological stressors, including diseases, yet their structure and scale offer great challenges to study at large scales. Several emerging technologies provide exciting new approaches to more readily monitor and analyze plant health, advancing the study and management of plant diseases in wildlands (Nelson, 2004; Duarte et al., 2022).

Disease ecology research deepens our understanding of the ecological roles of interactions among infectious agents, host organisms, and their environment. Wildland plant diseases can drive natural selection, fostering disease-resistant plant species that enhances overall resilience, while also contributing to nutrient cycling through decomposition (Alexander, 2010). However, plant diseases can also harm biodiversity, ecosystem functions, and economic stability, particularly when exacerbated by climate and land use changes (Patz et al., 2008). Forest diseases can diminish forest health, cause economic setbacks due to resource decline, disrupt essential ecosystem services, and enhance susceptibility to future environmental stressors.

Emerging technologies, like remotely piloted aircraft (i.e., drones) and artificial intelligence (AI), hold significant potential for addressing challenges related to wildland disease detection, monitoring, and management (de Castro et al., 2021). Drones equipped with advanced sensors and cameras can survey large forested areas, capturing high-resolution data that can be analyzed using AI algorithms to identify host plant species and detect signs of disease even before the appearance of extensive symptoms. These technologies enable rapid monitoring of forest health (Dash et al., 2017), high-resolution remote sensing capable of detecting subtle changes in plant health (Fraser & Congalton, 2021), predictive modeling for disease outbreaks (Shivaprakash et al., 2022), and precision application of control treatments (Fardusi et al., 2017). A drone's ability to access remote areas, coupled with AI's data processing power, can support efficient and cost-effective solutions, ultimately aiding informed decision-making and proactive disease management strategies.

I designed my ecological research around the concept of the disease triangle, a conceptual framework used to explain the interactions that lead to the development of plant diseases (Scholthof, 2007). The disease triangle has three interconnected components: a susceptible host plant, a virulent pathogen, and an environment conducive to their interactions. The disease triangle emphasizes the importance of the interaction between all three components for pathogen spread and disease development. This concept is crucial for disease management strategies, as it highlights the potential points of detection and intervention. By modifying the environment, increasing host resistance, or controlling the pathogen, it's possible to disrupt the disease triangle and reduce the incidence and severity of plant diseases. The social dimension of disease management adds an additional layer of complexity by considering how human activities influence disease dynamics. Human activities, such as logging, urbanization, and agricultural expansion, can alter wildland ecosystems and facilitate pathogen transmission. Changes in land use and management practices can alter the distribution and abundance of susceptible hosts and virulent pathogens, allowing the emergence of novel diseases or epidemics of otherwise minor pathogens. Additionally, the movement of plant material via global trade networks can introduce new pathogens to wildland areas and facilitate the rapid spread of invasive pathogens to previously uninfested regions.

In Chapter 2, I focus on developing a method for mapping the distribution of host plants using drones and AI. Wildland conservation efforts require accurate maps of plant species distribution across large spatial scales. High-resolution species mapping is difficult in diverse, dense plant communities, where extensive ground-based surveys are labor-intensive and risk damaging sensitive flora. High-resolution satellite imagery is available at scales needed for plant community conservation across large areas but can be costly and lacks adequate resolution to identify plants to species. Deep learning analysis of drone-based imagery can aid in accurate classification of plant species in these communities across large regions. I assessed the effectiveness of drone-based imagery and deep learning modeling approaches to map woody plant species in complex chaparral, coastal sage scrub, and oak woodland communities. I tested the effectiveness of three analytical approaches – random forest, support vector machine, and convolutional neural network (CNN) coupled with object-based image analysis (OBIA) for mapping in diverse shrublands. The CNN + OBIA approach outperformed random forest and support vector machine methods to accurately identify tree and shrub species, vegetation gaps, and communities. It was even able to distinguish two congeneric shrub species with similar morphological characteristics. Similar plant-identification accuracies were attained when applied to neighboring sites. This work demonstrates the ability of using drone imagery and deep learning analysis to accurately identify woody species and vegetation mapping at the large scales needed for conservation research and monitoring in chaparral and other wildland plant communities.

After identifying the distribution of host plants, I turned to examining associations between the spatial distribution of foliar plant disease and an environmental condition required for disease development – the duration of surface leaf wetness. Leaf wetness and air temperature play crucial roles in the dispersal, infection, and development of plant pathogens (Huber & Gillespie, 1992). The monitoring of leaf wetness and air temperature can support early disease detection and management (Rowlandson et al., 2015). However, measuring surface leaf wetness in expansive wilderness plant communities poses several formidable challenges. These challenges stem from the remote and often unpredictable nature of these environments. They encompass issues associated with data retrieval from multiple stations, interference from wildlife, and the environmental impacts of monitoring activities. To overcome these hurdles, researchers employ approaches that combine the use of field sensors, remote sensing technologies, and advanced leaf wetness modeling strategies to effectively collect, interpret, and apply epidemiological models across larger landscapes. In Chapter 3, I compared the effectiveness of nine popular machine learning algorithms and four simple, conventional empirical threshold models to characterize patterns of leaf wetness duration across a spatially heterogeneous region of a temperate maritime wildland ecosystem. I identified suitable machine learning algorithms for estimating leaf wetness and propose that the use of simple empirical models based on dew point depression or relative humidity thresholds perform well compared to machine learning techniques. I applied these models across the landscape during the coastal summer fog season when frequent leaf surface wetting and seasonably warm temperatures can create a favorable environment for the development of fungal diseases. Lastly, I relate interpolated leaf wetness duration to patterns of disease-related dieback in two species of endemic manzanita shrubs with differing distributions. I found that canopy dieback symptoms were more prevalent and severe in *Arctostaphylos tomentosa* at coastal sites, where leaf wetness durations were longer. In contrast, canopy dieback in *A. pumila* was consistent throughout its coastal to inland range. Morphological traits and endemic ranges of the two species may explain differences in disease responses.

In Chapter 4, I explore the historical, legal, policy, and training aspects of drone use that inform how to achieve civil aviation safety and privacy protection while not impeding their beneficial uses. I first summarize the legislative history of civilian drone integration in the U.S. national airspace. Next, I explore the current regulatory frameworks with a focus on federal safety requirements for commercial pilots and the evolving landscape of state statutes that address drone aerial trespass and privacy rights issues. I highlight key court cases that have shaped current legal precedent and subsequent protections for unreasonable drone aerial invasions of privacy in the U.S. national airspace. Lastly, I explore the potential strengths and challenges of a federal-state drone regulatory status quo. My work in Chapter 4 revealed a persistent federal-state tension regarding privacy legislation that points to the need for drone pilots to demonstrate an understanding of federal safety regulations and state privacy laws. In Chapter 5, I examine the current federal certification framework that evaluates pilots' knowledge of safe and legal flying, and identify the lack of training on privacy ethics and drone pilot best practices for maintaining transparency. Expanding professional certification beyond the federal program can support standards and training across federal and state jurisdictions that address issues of privacy and methods of reducing impacts of commercial drone operations. In this chapter, I examine how non-profit organizations can provide an accredited certification for a commercial pilot training solution that assesses safety and privacy concerns. I also explore how such a certification can be administered through existing commercial and higher-education collaborations.

This dissertation offers several noteworthy contributions to the fields of plant disease ecology, machine learning, and conservation applications for drone technology. Firstly, it introduces an innovative method for the large-scale mapping of host plant species distribution using drone-based imagery coupled with deep learning techniques. This approach has the potential to expand our ability to monitor and understand plant disease dynamics in diverse wildland plant communities. Secondly, this dissertation examines the relationship between plant diseases and leaf wetness patterns using machine learning algorithms and empirical models. It offers compelling evidence that simpler empirical models can be just as effective as more complex machine learning methods in assessing this association, thus providing valuable insight and pragmatic computational tools for disease management. Furthermore, the dissertation provides compelling evidence of a correlation between leaf wetness and disease-related dieback in two endemic shrub species across varying climatic conditions. This finding contributes to our understanding of the ecological factors influencing plant health in coastal shrublands. In addition to its ecological contributions, the dissertation also explores the legal and regulatory dimensions of drone usage, focusing on federal and state regulations. It identifies key tensions between federal and state privacy legislation in this context, shedding light on the complex legal landscape surrounding drone technology. Lastly, the dissertation proposes a forward-thinking enhancement to professional drone pilot certification programs. It suggests the inclusion of training modules on privacy ethics and security best practices for drone pilots. This recommendation reflects a proactive approach to addressing emerging ethical concerns and ensuring responsible drone operation in an evolving technological landscape. Together, these contributions offer a comprehensive and interdisciplinary exploration of topics at the intersection of ecology, technology, and legal frameworks.

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# Chapter 2

# Using Deep Learning and High-Resolution Drone Imagery to Accurately Identify Diverse Shrub Species in California Coastal Communities

## 2.1 Introduction

Accurately mapping, assessing, and monitoring terrestrial vegetation is central to ecological and global change research (Miller & Rogan, 2007). Current methods are too costly or laborious to cover large areas. Remote sensing constructs images of the physical characteristics of an area by measuring its reflected and emitted radiation at a distance using special sensors (Schowengerdt, 2006). Land cover of vegetation or other physical objects is commonly mapped using those remote sensing data to then construct classification models based on observed spectral and structural relationships, validating the land cover classifications based on a minimum mappable unit, determined by the available resolution of remotely sensed imagery. Satellites and aircraft provide valuable remote sensing data that are used in plant ecological research at regional and global scales but these systems are often limited in their capacity to provide images at the spatial, temporal, and spectral resolution needed to support research at finer ecological scales (i.e., species, populations) (Sun et al., 2021). Affordability can also be an issue when researchers need high resolution satellite or aerial imagery across large areas (Turner et al., 2015). Plant ecological research at finer scales often relies on approaches that use handheld sensor systems mounted to ground-mounted systems (e.g., poles, cranes, towers). The logistics of these ground-based measurements is often too time consuming and physically challenging to collect more than a limited number of samples or to apply them to more complex systems or over large geographic ranges. Additionally, such ground-based surveys are arduous, dangerous, and risk damaging sensitive flora in wildland habitats with diverse, dense plant communities (Questad et al., 2022). Such challenges mean that ground-based sensing surveys in shrubland and forest communities are often very labor intensive, limited in spatiotemporal resolution, and prone to under-sampling.

Lightweight uncrewed aerial vehicles (UAVs), also called drones, are increasingly used as a remote-sensing platform in plant ecology. Their flexibility, reduced cost, reliability, autonomous capability, and high-resolution multispectral and structural data contribute to their usefulness in a variety of wildland systems at finer scales than spaceborne satellite or crewed aircraft imagery (J. Zhang et al., 2016; Guimarães et al., 2020). UAV data can also complement data collected using ground-based observations (Atkins et al., 2020), satellites (Dash et al., 2018), and crewed aircraft surveys (Mangewa et al., 2019).

Advances in UAV hardware, coupled with developments in three-dimensional (3D) point cloud modeling of landscape structure using Structure-from-Motion (SfM) algorithms are providing an alternative to expensive LiDAR platforms for structural mapping (D'Urban J et al., 2020). Light detection and ranging (LiDAR) sensor systems are among the most accurate for measuring structural attributes at the stand and individual canopy levels (Wallace et al., 2016; Dalponte et al., 2012), but the high equipment costs can make LiDAR sensors difficult to procure. Structure-from-Motion (SfM) photogrammetry is a computer vision technique that constructs a 3D model from a set of overlapping two-dimensional (2D) digital photographs (Westoby et al., 2012). UAV-derived photogrammetric point clouds (PPCs) generated from drone photographs and structure-from-motion (SfM) algorithms provide an analogous three-dimensional (3D) structural measurement and are gaining popularity as a low-cost and accurate alternative to characterize ecologically relevant landscape structure including the shapes and sizes of trees and shrubs (Wallace et al., 2016; D'Urban J et al., 2020). SfM approaches coupled with spectral analysis have been used to identify tree species (Onishi & Ise, 2021), assess small-scale tree canopy gaps (Getzin et al., 2014) and estimate biomass in low stature grassland vegetation (Wijesingha et al., 2019).

Shrublands have gained attention because of the ecosystem services they provide (Brunson, 2014; Liu et al., 2014; Wohlgemuth & Lilley, 2018; Gonzalez M et al., 2020), their increased vulnerability to global change (i.e., drought, fire, land use change) (Vicente-Serrano et al., 2012; D. Li et al., 2018; Jacobsen & Pratt, 2018), and efforts to conserve and actively restore degraded shrublands in Mediterranean-type ecosystems (Lecina-Diaz et al., 2019; Syphard et al., 2018; Underwood et al., 2022), subtropical regions (J. Li et al., 2016), and deserts (Wang et al., 2020). This has spurred interest in applying UAV surveys in shrublands, but advances have been limited by the set of challenges related to quantifying the spatial distribution of species. Canopies in these ecosystems should be readily accessible given their low stature, but in many of the more diverse and spatially heterogeneous shrublands, dense and impenetrably overlapping canopies can limit physical access, increase risk to workers, and risk significant damage to sensitive flora. In more arid, spatially diffuse desert shrublands, mapping species distribution and quantifying biomass with satellite imagery is possible but with large uncertainties and logistically challenging field validation (Zandler et al., 2015). UAVs have been successfully used in sensitive shrubland habitats to map plant community structure (Gonzalez M et al., 2020; Charton et al., 2021), estimate biomass (Doughty & Cavanaugh, 2019; Ding et al., 2022), map species distribution in highly dynamic environments (Zhao et al., 2020), and augment the assessment of restoration success (Al-Ali et al., 2020).

Chaparral shrublands are the dominant wildland vegetation type in Southern California and one of the most extensive ecosystems in California, with evergreen sclerophyllous shrubland cover making up approximately 9% of the state (Underwood et al., 2018). Satellite remote sensing has been used for vegetation classification in

California coastal shrublands at the stand and community scale (Roberts et al., 1998), can distinguish perennial woody from herbaceous annual vegetation within a shrubland community (Hamada et al., 2011), and can estimate aboveground biomass of dominant species (Underwood et al., 2022). Recent work utilized aerial imagery and LiDAR data from airplane flights to classify coastal scrub communities in terms of vegetation alliances and associated species with limited success due to interference from variable topography and available light conditions (Warkentin et al., 2020) No studies have explored the use of UAVs data and machine learning approaches to classify woody-plant species at the level of individuals or patches in chaparral and scrub communities, as required to support ecological research.

Conventional land-cover classification maps are constructed from remotely sensed data using one of two general image analysis approaches: pixel-based classifiers and geographic Object-Based Image Analysis (OBIA) methods. Pixel-based classification approaches use spectral information associated with individual pixels, irrespective of their spatial distribution and land cover context to assign land cover classes. Pixel-based methods of image classification can further be separated into two classification approaches - unsupervised or supervised. Unsupervised pixel-based approaches group pixels into clusters based on their properties and classify each cluster with a land cover class independent of the researcher. Unsupervised pixel-based methods can be computationally faster and the automated nature of the approach does not require the researcher to provide contextual samples to constrain the classification process. Although faster, unsupervised pixel-based classification approaches often produce unsatisfactory results especially when remote sensing data has a very high spatial resolution and objects of interest have high pixel heterogeneity – producing classifications that resemble what researchers term the "salt and pepper effect" (Weih & Riggan, 2010).

Pixel-based approaches can also be supervised to control the relevance and accuracy of classification. In a supervised pixel-based classification approach the researcher selects representative samples for each of the land cover classes of interest in an image. Samples are used to generate signature files that store the samples' spectral information and this information is used to make classifications by running a classification algorithm (e.g., support vector machine). With the increased availability of high-resolution remote sensing data, software developers and researchers have moved to the use of semi-automated OBIA classification procedures that analyze the spectral, spatial, and contextual properties of imagery pixels and use segmentation processes with iterative machine-learning algorithms to delineate objects in the landscape that can then be systematically classified. OBIA classification approaches group pixels into representative geometries based on a set of parameters designated by the researcher. These parameters are based on the scale, shape, texture, spectral properties, and geographic context of objects of interest (Blaschke et al., 2014). The OBIA classification process is supervised, requiring input of samples that have been previously classified by humans to complete the classification process.

The use of artificial intelligence (AI) approaches for land-cover classification and mapping has a well-established history, particularly for satellite-based remote sensing (Civco, 1993). Much of the success from AI in remote sensing has been in advancing the use of image processing and pattern recognition as improvements over conventional statistically-based procedures for classification of landscape features. Advances in graphics processors, classification algorithms, and the increased ability of artificial neural networks to accurately and efficiently classify imagery using multiple layers of features have driven a surge of interest in AI approaches to land cover classification. These deep learning approaches examine the intricate pixel-based structure in very large image datasets using a backpropagation algorithm that allows the machine to adjust its internal parameters to compute an accurate representation in each layer of its neural network based on the representation in the previous layer.

Recent research has determined that non-parametric decision tree machine learning algorithms namely, random forest (RF) and support vector machine (SVM), are well suited to classify vegetation species using high-resolution multispectral and RGB UAV imagery (Garzon-Lopez & Lasso, 2020). The RF algorithm in particular is regarded as an effective classification modeling approach for remote sensing data in complex landscapes given its classification accuracy and high predictive stability compared to other approaches (De Castro et al., 2018; Franklin & Ahmed, 2018) given the ability to tune model parameters accurately and robustly (T. Zhang et al., 2022), while decreasing the probability of an overfitted machine learning model (Hastie et al., 2009). Support vector machines (SVMs) are a machine learning tool that approach a higher rate of accuracy than random forest (Bell, 2014), but SVM classification accuracies can be reduced when the identification of target classes requires multiple high resolution imagery bands.

One of the most successful deep learning classification approaches in vegetation remote sensing is the convolutional neural network (CNN) (Kattenborn et al., 2021). CNNs utilize computational models that are made up of multiple convolved layers that learn representations of data using multiple levels of mathematical abstraction (LeCun et al., 2015). The neural network is made up of 'hidden-layers' composed of two stages. In the first stage, the network completes a convolution of the previous layer at a particular kernel size and is able to store trainable weights. The second stage is a max-pooling stage which aims to reduce the number of computational units by keeping only the most responsive kernel units derived from the first stage convolution. CNNs can consist of multiple convolutional and max pooling layers that end in a fully connected layer that receives input from all of the units from the previously hidden layer and has a decision unit for each class that the network can predict. In remote sensing applications, the most common form of CNNs uses a supervised learning approach and requires a series of labeled training input images containing a subject of interest, assigned by the researcher, that the computer can then use to assign importance to a variety of image attributes. Ultimately the computer assigns learned weights that can be used to classify future imagery that was not part of the original training set. Two key advantages of CNN techniques are that it requires very little computational engineering and the approach can easily take advantage of the increased amount of available graphical processing power to process very high-resolution UAV data. CNNs achieve this by systematically reducing images into a data form that is easier to computationally process without losing features that are critical for accurate classification. Once the CNN is trained it can be applied to classify an entire raster landscape. Applying the CNN model results in a spatially explicit probabilistic heat map for each classification. The assignment of a discrete classification to map regions can be achieved using fuzzy logic classifiers and a geographic object-based image analysis workflow (OBIA). CNN and OBIA approaches have demonstrated high classification performance on a variety of plant species classification applications in agriculture (Dyrmann et al., 2016; Kamilaris & Prenafeta-Boldú, 2018) and forestry (Hafemann et al., 2014; Schiefer et al., 2020). Additionally, CNN approaches have been successful in detecting low-stature shrub species in a variety of plant communities (Guirado et al., 2017; Frost et al., 2021; James & Bradshaw, 2022; Tamiminia et al., 2021). Recently, CNN deep learning modeling has been combined with the OBIA classification approach, a process now termed CNN fusion (i.e., CNN+OBIA, CNN+GEOBIA, OCNN), with the aim of improving the overall accuracy of land cover classification by implementing an OBIA segmentation of CNN classification probability output (Timilsina et al., 2019; Martins et al., 2020).

A robust methodology for species-level classification in complex shrublands can greatly increase the possible spatial and temporal extent of species-level monitoring for conservation and restoration, species-specific stand-level health assessments, fire risk and fuel load assessment, and biomass and carbon sequestration modeling. We posit that a CNN machine learning approach coupled with OBIA can leverage the high-resolution multispectral and structural data from UAV flight surveys to efficiently and accurately classify shrub species canopy across landscapes. This study demonstrates how shrub and tree species in spatially heterogeneous stands of chaparral, coastal sage scrub, and oak woodland can be accurately classified and mapped using drone-based multispectral imagery and a CNN+OBIA supervised machine learning classification approach.

## 2.2 Methods

### Study Site

All research occurred on the 246-ha University California, Santa Cruz - Fort Ord Natural Reserve (UCSC-FONR) (Figure 2.1).The UCSC-FONR is located approximately 129 km south of San Francisco, CA. along the Monterey Bay and bordered by the city of Marina. This coastal parcel includes an abundance of low-growing shrublands among accessible rolling terrain (96-ha), ranging in ele-

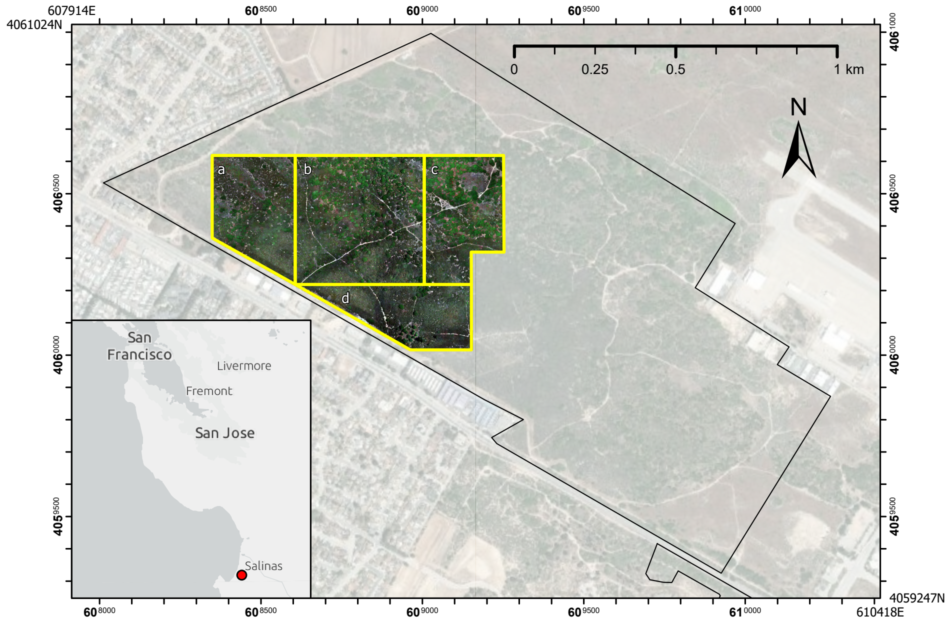


Figure 2.1: Map of research sites (yellow border) - UCSC Fort Ord Natural Reserve (black border). a) Application Site 1 (8.42ha), b) Training Site (16ha), c) Application Site 2 (8.84ha), d) Application Site 3 (7.44ha). Backdrop imagery source: World Imagery Esri, Maxar, Earthstar Geographics (2022). Research site imagery is displayed as RGB orthomosaic from UAV research flights.

vation between 21 to 58 meters above mean sea level. We focused on a 40.7-ha area in the northwestern region of the reserve that includes a mosaic of three woody plant dominated coastal plant communities typical of the semi-arid coastal Mediterranean-type ecosystems of central California: maritime chaparral, coastal sage scrub, and coastal live oak woodland (Figure 2.2).

Maritime chaparral is a plant community found along the central California coastline and is characterized by sclerophyllous shrub species with hard, waxy-cuticle leaves. Dominant taxa in this community include manzanita species (*Arctostaphylos tomentosa* and *A. pumila*), chamise (*Adenostoma fasciculatum*), and a rare California lilac (*Ceanothus rigidus*). Coastal sage scrub is characterized by its drought-deciduous aromatic shrub species adapted to coastal lowlands in Mediterranean climate regions. Species associated with coastal sage scrub include California sagebrush (*Artemisia californica*), black sage (*Salvia mellifera*), coyote bush (*Baccharis pilularis*), and mock heather (*Ericameria ericoides*). Monotypic stands of coast oak woodlands (*Quercus agrifolia*) are surrounded by stands of maritime chaparral and coastal sage scrub. Some species are found in multiple plant communities (e.g., poison oak, *Toxicodendron diversilobum*) and several species can be intermixed at small scale. Four sites were determined based on the dominance of 10 of the 53 woody plant species known to occur in the region.(Table 2.1)

Table 2.1: Summary of the dominant woody plant species in the study sites and their associated plant communities. *Arctostaphylos tomentosa* ssp. *tomentosa* is referred to as *A. tomentosa* throughout this manuscript. Some species are known to inhabit all communities (e.g., *T. diversilobum*) and some coastal sage scrub species are known to encroach into mixed chaparral and coastal sage scrub.

| Species | Common name | Plant Communities |
|---|---|---|
| *Adenostoma fasciculatum* | Chamise | Maritime Chaparral |
| *Arctostaphylos pumila* | Sandmat Manzanita | |
| *Arctostaphylos tomentosa* | Woolyleaf Manzanita | |
| *Ceanothus rigidus* | Monterey Ceanothus | |
| *Artemisia californica* | California Sage | Coastal Sage Scrub |
| *Baccharis pilularis* | Coyote Brush | |
| *Ericameria ericoides* | Mock Heather | |
| *Salvia mellifera* | Black Sage | |
| *Toxicodendron diversilobum* | Poison Oak | |
| *Quercus agrifolia* | Coast Live Oak | Oak Woodland |

### UAV Data Collection

UAV flight data were acquired in Summer 2021 (7/23/2021 - 7/24/2021), under high cloudy overcast skies, no fog, and light winds (2-5 km/hr). We conducted five flight surveys ranging in area from 5-9 ha (Figure 2.1) All flights were approximately 30 minutes in duration and conducted near solar noon (1100 - 1300 PDT). Overcast conditions were ideal for limiting shadows created by taller neighboring vegetation that tend to obscure lower growing vegetation. All automated flight operations were planned and executed using DJI Pilot (v2.3.1.5) software as single pass grid flight patterns with 80% frontlap and at least 80% sidelap at a constant altitude of 60 m above the terrain to ensure the desired ground sampling distance (GSD; the distance between the centroids of two adjacent pixels measured

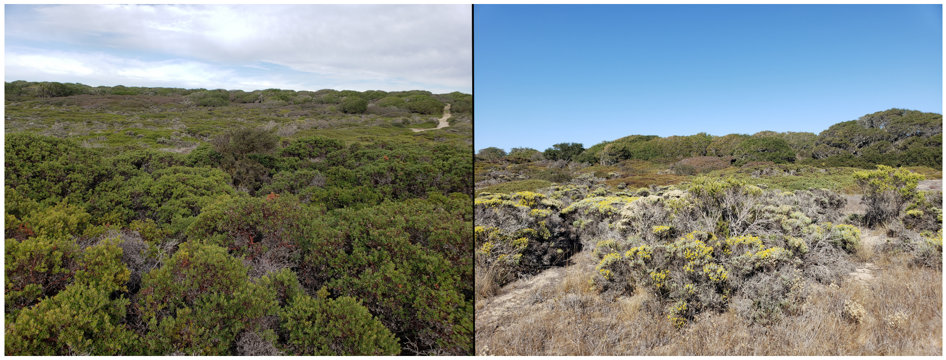

Figure 2.2: Manzanita dominated maritime chaparral (left) and coastal sage scrub transitioning to oak woodland (right). UCSC Fort Ord Natural Reserve, California.

on the ground). All flights were conducted by Section 107 FAA licensed pilots and in accordance with all federal, state, and local laws and regulations as well as all UC policies regarding small Uncrewed Aircraft System (sUAS) operation (UC-RK-18-0377).

A DJI Matrice 210 RTK V2 Pro quadcopter (DJI, Shenzhen, China) with approximately 30 minutes of flight autonomy was equipped with dual gimbals to accommodate two sensor systems capable of maximizing ground sampling distance (GSD) while capturing high resolution narrow spectral band reflectance data. A Zenmuse X7 24mm RGB camera with F2.8 leaf shutter aspheric lens captured high resolution imagery (GSD: 1cm/pixel, 24MP resolution) and was used in the generation of topographic rasters. The DJI Zenmuse X7 camera was connected to the onboard RTK-GNNS positioning system and WiFi connected to a DJI D-RTK Mobile Station which served as a high-precision GNSS ground receiver, providing real-time differential corrections of imagery position with centimeter-level positioning accuracy. The use of RTK correction negated the need for including ground control points in the sites. A MicaSense Altum multispectral sensor (MicaSense, Seattle, WA) collected calibrated narrow spectral band reflectance data at Blue (455-495 nm), Green (540-580 nm), Red (658-678nm), Red edge (707-727 nm), and Near infrared (800-880 nm) at GSD 2.5 cm/pixel. The RTK system was not compatible with logging positioning information to two image sensors so we used the MicaSense Altum sensor's integrated GPS to record image positioning and later georeferenced Altum multispectral rasters to the reference RTK-collected Zenmuse X7 RGB data.

### UAV Image Processing

UAV imagery was photogrammetrically processed using Pix4DMapper Pro (v4.6.4) software (Pix4D SA, Lausanne, Switzerland) to generate multispectral orthomosaic and topographic rasters. An orthomosaic raster is an image generated from a mosaic of multiple georeferenced overhead images corrected for perspective and scale. Additional orthorectification of the multispectral raster to the reference Zenmuse X7 imagery was completed using the Auto Georeferencing function in ArcGIS Pro (v3.0.0, ESRI 2022). The Auto Georeferencing function in ArcGIS Pro requires two rasters with similar band structure and automates the selection of georeferencing control points that can be exported and used to georectify additional reflectance rasters. We generated an RGB composite orthomosaic raster from the Zenmuse X7 and Altum data and georeferenced the Altum RGB raster dataset to the X7 RGB raster dataset and exported the control points generated by the auto georeferencing function. These control points were used to georectify the remaining calibrated near-infrared and near-infrared edge reflectance rasters generated from the Altum Micasense sensor.

Topographic rasters included digital surface models (DSM) and digital terrain models (DTM) generated from Zenmuse X7 imagery and rendered point cloud data. DSM raster generation utilized a point cloud densification workflow with optimization at ½ image size and an inverse distance weighting algorithm application. DTM raster generation was achieved using a point cloud classification algorithm and gaussian averaging producing a terrain model with lower resolution (5 cm/pixel). We used QGIS (v3.20.1-Odense) to generate a vegetation canopy height model from the normalized digital surface model (nDSM) by taking the arithmetic difference between the DSM and DTM raster values. We also calculated the slope values as a raster from the resulting nDSM. The percent slope model showed the maximum rate of elevation change between each cell and its neighbors calculated as the angle of inclination to the horizontal. Percent slope can be used to find the borders of overlapping tree canopies and gaps (Onishi &

Ise, 2021) and may support distinguishing between shrub species that have overlapping canopies as well as gaps in canopy. The slope raster was generated using the GDAL DEM utility in QGIS. All raster products were exported as 32-bit and 8-bit GeoTIFF format with WGS 84 / UTM zone 10N (EGM 96 Geoid) projection. A 64-bit Windows 10 PC equipped with an Intel® Core™ i9-10900KF CPU at 3.70GHz, 32GB RAM, and an NVIDIA GeForce RTX 3060 graphics processor was used for all photogrammetric processing and machine learning modeling.

### Flight Imagery

We successfully generated a multispectral orthomosaic (2.5 cm/pixel; Figure 2.3), nDSM (5 cm/pixel; Figure 2.4), and a slope raster (Figure 2.5) for the entire research site (40.7 ha).

### Field Sampling

Between Summer 2021 and Summer 2022 we completed extensive ground surveys of woody vegetation across the four study sites. During the yearlong period of surveys, we did not find any significant changes in the spatial distributions of the vegetation alliances and shrub species. Given the dense, often impenetrable canopies we opted for a plotless sampling technique over transect or quadrat sampling methods. Previous surveys of the entire natural reserve have documented the presence of 53 woody plant species with dominance by 10 species. To acquire ground positions of woody plant species, we uploaded an 8-bit version of the high-resolution X7 RGB orthomosaic imagery from UAV flights to an Android tablet mobile device and accessed imagery in the field using the open-source GIS plugin QField (OPENGIS.ch, 2020). The QField interface was configured in QGIS Desktop to include a data collection form that allowed field technicians to efficiently collect GPS point data on the position of woody plant species by referencing imagery in real time relative to their current ground position. GPS point data was collected for areas that were distinguishable in the imagery, larger than $0.5m^2$ and consisting of a single live species, bareground, or standing deadwood. Technicians recorded cover type and ensured that survey points were separated by distances

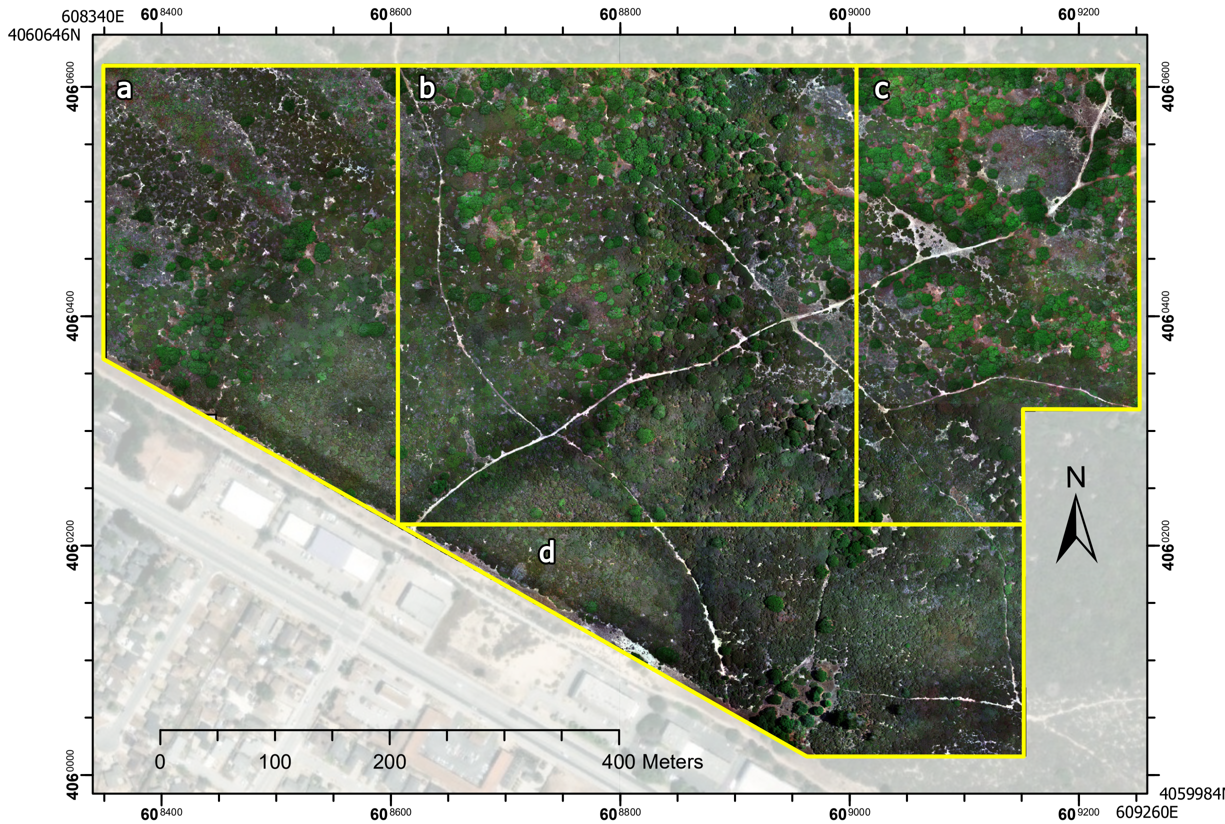


Figure 2.3: Orthomosiac raster displayed in RGB. a) Application Site 1 (7.43ha), b) Training Site (16ha), c) Application Site 2 (9ha), d) Application Site 3 (8ha). Resolution 2.5 cm/pixel with WGS 84 UTM Zone 10 projection.

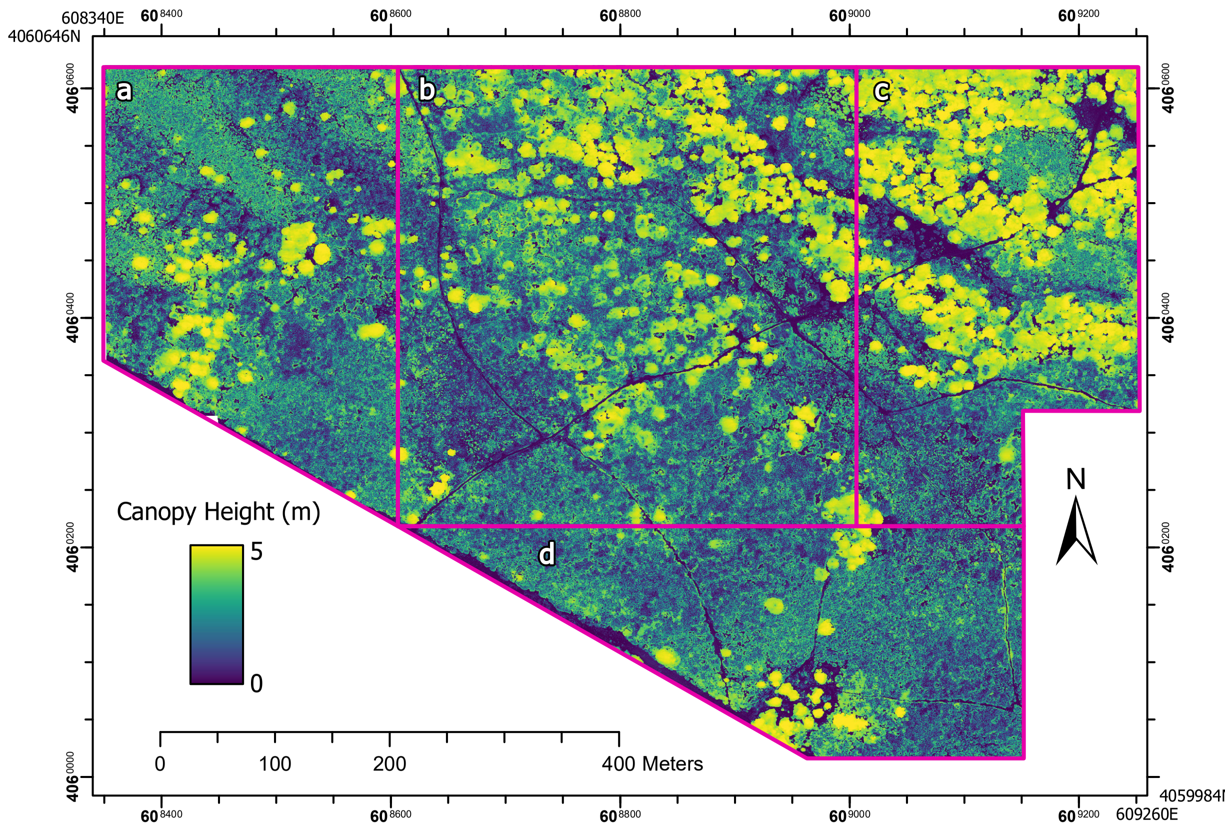


Figure 2.4: Normalized Digital Surface Model (nDSM) estimating canopy height (m). a) Application Site 1 (7.43ha), b) Training Site (16ha), c) Application Site 2 (9ha), d) Application Site 3 (8ha). Resolution 5cm/pixel (WGS 84 UTM Zone 10 projection).

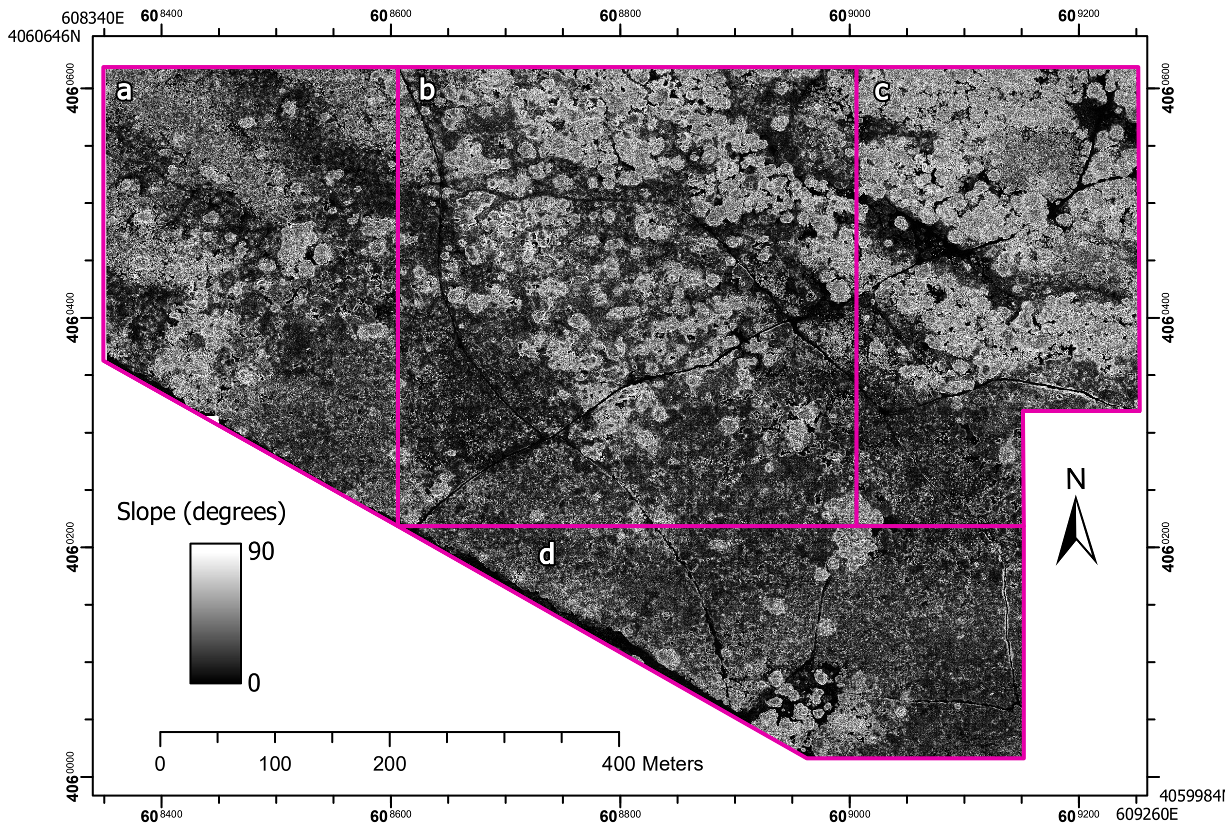


Figure 2.5: Slope model (degrees) generated from normalized digital surface model (nDSM) canopy height (WGS 84 UTM Zone 10 projection). a) Application Site 1 (7.43ha), b) Training Site (16ha), c) Application Site 2 (9ha), d) Application Site 3 (8ha).

of at least 3 meters. All geodata was synchronized via the QField plugin in QGIS desktop and stored in shapefile format.

We had a primary research interest in identifying individual species within the maritime chaparral plant community. We did not consolidate these species into a single classification category given management interests aimed at mapping the species distributions, assessing plant health, and estimating fuel loadings in the future. Manzanita, *Ceanothus*, and Chamise have very different fire-related characteristics (Zhou et al., 2005). To facilitate the focus on classification of those maritime chaparral species we lumped all the species comprising the coastal sage scrub community into a single broad category; this eliminated the need for additional algorithms for deeper species-level classification. Creating this broader coastal sage scrub category also tested the ability of machine learning approaches to classify a group with high spectral variability at the same time as species-specific classifications with lower spectral variability.

### Classification Modeling Development

We evaluated three OBIA integrated classifier methods: Random Forest (RF), Support Vector Machine (SVM), and a deep learning Convolutional Neural Networks (CNN) approach. All classifier methods were developed and applied into an object-based image analysis (OBIA) framework using eCognition Developer 10.2 software (Trimble Geospatial GmbH: Munich, 2021). eCognition Developer is a development environment designed specifically to combine machine learning approaches with object-based image analysis through analysis workflows called rule sets. Two key advantages of this approach are (1) CNN integration based on Google's TensorFlow API and (2) the ability to utilize the same OBIA landscape segmentation algorithms across the three classifier methods.

### Image Sampling

In order to generate training and testing sample patches, survey points in the 16ha training region (Figure 2.1) were randomly assigned to 70% training and 30% testing groups and labeled by membership to one of eight classification groups: *A.*

*fasciculatum*, *A. pumila*, *A. tomentosa*, *C. rigidus*, *Q. agrifolia*, a Coastal Sage Scrub group, Deadwood, and Bareground. Survey points with distances to the raster scene border of less than 12 pixels were not used to generate samples. Samples were generated by rendering a square polygon buffer around ground survey points with sides of 0.6m (0.36$m^2$) ground sampling distance (GSD), corresponding to 24x24 pixels image space, where each pixel represents 2.5cm GSD. Samples were extracted from 8-bit multispectral rasters (i.e., red, green, blue, near-infrared (NIR), and near-infrared edge (NIRe)). Deep learning methods require thousands of training samples and this is often achieved by systematically rotating the scene orientation that sample patches are extracted from. This method can also rectify problems associated with the influence of shadow orientations. We used eCognition Developer 10.2 (Trimble Geospatial GmbH: Munich, 2021) to create a fully automated process that rotates the raster imagery at an interval of 30-degrees, extracts 1,000 samples, and repeats the process a total of 12 times. The process generates 12,000 samples per class and a total of 96,000 samples across the 8 cover classes.

Our convolutional neural network architecture began with random initial weights and received sample patches from the five multispectral image layers as training inputs with the goal of generating a probabilistic heat map of cover classes as an output. The model consists of two batch normalized hidden layers. In the first hidden layer imagery is convoluted with a kernel size of 3x3 pixels and assigned to 40 feature maps without max pooling. In the second fully connected hidden layer, results from the first hidden layer are further convoluted using a 3x3 kernel size and assigned to 20 feature maps. Our CNN model consists of only the two hidden layers with no max pooling layers included. Max pooling is a method of reducing the pixel dimensions of the image thereby speeding processing time. CNN training was initiated by randomly shuffling training data and learning occurred at a rate of 0.0001 with 8,000 training steps, and a sample batch size of 100 images. Learning rate defines the amount by which weights are adjusted in each iteration of the statistical gradient descent optimization.

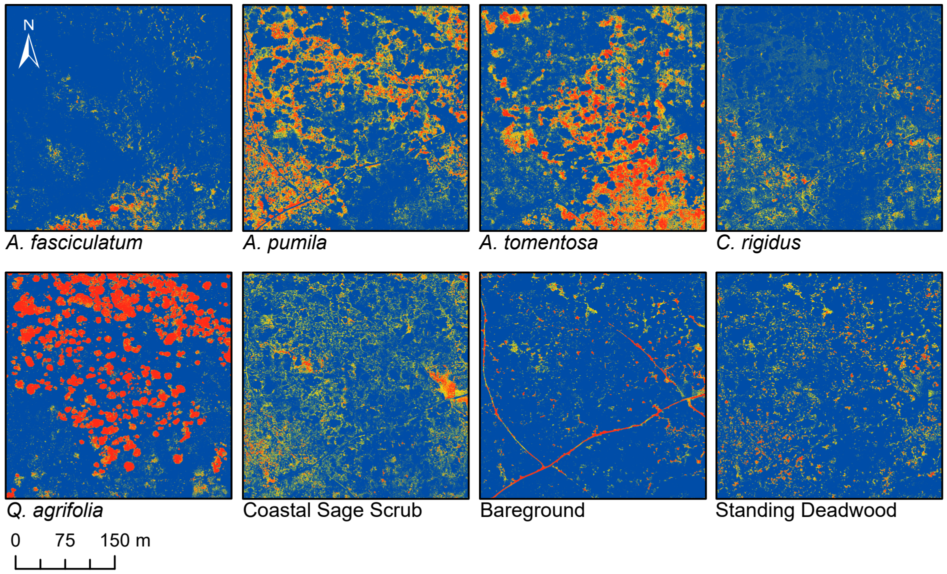


Figure 2.6: CNN generated probability heat maps for each feature class in the 16ha training site. Red regions have a high probability (p=1) of membership to the class and blue represents a null probability ($p = 0$) of membership to the feature class.

### CNN Application and OBIA Classification

Once the CNN model was trained using training samples, we applied the model to the entire 16ha training site and to the neighboring application sites. For each of the cover classes, we generated a separate raster heat map representing the probability that each pixel has membership within the cover classes (Figure 2.6).

### Segmentation

Multi-Resolution Segmentation, or MRS, is a widely-used segmentation approach for OBIA classification with very-high-resolution (VHR) imagery (Chen et al., 2021). We used the MRS algorithm in eCognition Developer 10.2 to generate a segmentation vector layer for objectbased image classification. Multiresolution segmentation implements a method of segmentation known as region growing that iteratively merges neighboring regions with similar spectral and spatial heterogeneity based on thresholds defined by the researchers (Blaschke et al., 2004). Our segmentation process utilized the multispectral orthomosaic, canopy height (nDSM), and slope model as inputs with weightings assigned through trial and error as multispectral (4), canopy height (2), slope (1). Segmentation parameters were set to a scale of 80, shape of 0.2, and compactness of 0.6.

Next, image segmentations were classified by generating a class hierarchy based on fuzzy logic membership using eCognition Developer 10.2. Each feature class in the classification hierarchy contained a class description consisting of a set of fuzzy logic membership functions that evaluated the specific probabilistic features of the individual heat maps generated from the CNN. We defined all of the fuzzy sets by linear membership functions that identified a soft fuzzy classifier that uses a degree of membership probability to express an object's assignment to a class. The membership values range from 0.0 to 1.0, where 1.0 represents full membership to a feature class and 0.0 represents absolute non-membership. One advantage of these soft fuzzy logic methods lies in their ability to quantify uncertainties about the descriptions of feature classes and assign membership to a class based on the degree of uncertainty of membership in other classes. For this study, all membership functions varied between 0 and 1 except for *C. rigidus* which was assigned a heat map probability threshold for classification that began at 0.85 instead of zero. This threshold was based on expert knowledge of where rare *C. rigidus* is actually located in the landscape and was determined by trial-and-error to accurately identify the species and reduce false positive classification.

To assess accuracy during model development in the 16ha training site, the 30% of randomly selected ground survey points were used to assign segmentation polygons as test classification polygons. If multiple ground survey test points of the same classification type were together in a test segmentation polygon, then we deleted test points so that only a single ground survey test point was associated with each testing segmentation polygon. Prior to testing we also ensured that training ground survey points were not within polygons that were assigned as test segmentation polygons. The overall impact of this process reduced the proportion of testing points by 1-2% per class and reduced the overall number of testing points total by 11% (Table 2.2)

Table 2.2: Number of ground survey points collected at each site

| | | Training Site | | | Application Site | | |
|---|---|---|---|---|---|---|---|
| Plant Community / Group | Cover Type | Training | Testing | Corrected Testing[a] | 1 | 2 | 3 |
| Maritime Chaparral | *Adenostoma fasciculatum* | 174 | 74 | 67 | 244 | 9 | 303 |
| | *Arctostaphylos pumila* | 1545 | 662 | 562 | 387 | 492 | 247 |
| | *Arctostaphylos tomentosa* | 1065 | 457 | 369 | 295 | 218 | 573 |
| | *Ceanothus rigidus* | 162 | 69 | 64 | 16 | 87 | 33 |
| Coastal Sage Scrub | *Artemisia californica* | 20 | 9 | 9 | 17 | 8 | 14 |
| | *Baccharis pilularis* | 84 | 36 | 34 | 48 | 31 | 23 |
| | *Ericameria ericoides* | 286 | 123 | 119 | 69 | 91 | 36 |
| | *Salvia mellifera* | 102 | 44 | 42 | 62 | 16 | 39 |
| | *Toxicodendron diversilobum* | 35 | 15 | 14 | 30 | 57 | 18 |
| Oak Woodland | *Quercus agrifolia* | 913 | 392 | 376 | 186 | 306 | 82 |
| Canopy Gaps | Standing Deadwood | 226 | 97 | 90 | 94 | 83 | 78 |
| | Bareground | 340 | 146 | 136 | 70 | 112 | 72 |
| | **Total Ground Points** | **4952** | **2124** | **1882** | **1518** | **1510** | **1518** |

[a] represents individual testing ground survey points within test segmentation polygons.

### Accuracy Assessment

The classification performance of CNN+OBIA, RF, and SVM methods was assessed using visual inspection of classified segmentation polygons and quantitative accuracy assessment as object-based calculations of overall accuracy (OA) and Cohen's Kappa coefficient ($\kappa$). In order to evaluate individual cover classes, we calculated per-class precision, recall, and F-Score (F1) statistics.

Precision (Aronoff, 1982), also called user accuracy, summarizes how often a real cover type on the ground (i.e., from reference data) correctly appears on the classified map. Recall, also called producer accuracy, describes how often the classes designated on the map are actually present on the ground.

A highly accurate classification must balance high recall and high precision. The F-Score (F1) statistic is a useful metric to evaluate that trade-off calculated as the harmonic mean of the precision and recall (Sundheim, 1992). A higher F1 statistic indicates support for predictions made by the model classifier. Another convention is to calculate Cohen's kappa coefficient ($\kappa$) which compares observed patterns to a classification based entirely on random assignment. Kappa values range from -1 to 1; a value of 0 indicates that the classification is no better than random, and $\kappa$ close to 1 indicates that the classification is better than random.

## 2.3 Results

### Field Survey Results

We collected a total of 11,622 ground survey points across the entire 40.7ha research area (Table 2.2) The majority of data collection (60%) was concentrated within the 16ha model training site, and the rest in the 24.7ha application sites.

### Classification Model Results

The CNN+OBIA method had the highest overall classification accuracy across all application sites ($Mean\ OA_{CNN+OBIA} = 0.85, Mean\ \kappa_{CNN+OBIA} = 0.81$) (Figure A.1) compared to random forest ($Mean\ OA_{RF} = 0.63, Mean\ \kappa_{RF} = 0.55$)

A.2) and support vector machine ($Mean\ OA_{SVM} = 0.67, Mean\ \kappa_{SVM} = 0.58$) (Figure A.3. Our CNN+OBIA approach accurately classified three species of chaparral shrub species in the application sites including: *A. fasciculatum* ($Mean\ \kappa_{CNN+OBIA} = 0.80$), *A. pumila* ($Mean\ \kappa_{CNN+OBIA} = 0.86$), and *A. tomentosa* ($Mean\ \kappa_{CNN+OBIA} = 0.72$). Random forest and SVM classification models were most effective at classifying *A. pumila* ($Mean\ \kappa_{RF} = 0.79$, $Mean\ \kappa_{SVM} = 0.91$), but only moderately accurate at classifying *A. tomentosa* ($Mean\ \kappa_{RF} = 0.45$, $Mean\ \kappa_{SVM} = 0.60$), and poor at classifying *A. fasciculatum* ($Mean\ \kappa_{RF} = 0.08$, $Mean\ \kappa_{SVM} = 0.21$). CNN+OBIA was the most effective model for classifying several other cover classes including: *Q. agrifolia* ($Mean\ \kappa_{CNN+OBIA} = 0.97$), bareground ($Mean\ \kappa_{CNN+OBIA} = 0.96$), standing deadwood ($Mean\ \kappa_{CNN+OBIA} = 0.89$), and coastal sage scrub ($Mean\ \kappa_{CNN+OBIA} = 0.69$). Rare *Ceanothus rigidus* classification accuracy was poor across all sites ($Mean \kappa_{CNN+OBIA} = 0.28$, $Mean \kappa_{RF} = 0.21$, $Mean \kappa_{SVM} = 0.21$). Complete confusion matrices (Figures A1-A3)and additional land cover classification maps (Figures A4-A6) are available in the Appendix A supplementary materials.

## 2.4 Discussion

Here we presented a CNN+OBIA classification modeling approach based on very high resolution multispectral and structural UAV data capable of accurately identifying species, broader plant communities, and structural cover features in complex, wild vegetation. We attribute the success in our CNN+OBIA classification process to three factors: consideration of target species abundances and distribution across the training and application sites, collection of extensive ground survey training data, and integration of a CNN workflow that uses high resolution multispectral data with object-based segmentation based on multispectral and structural data. One distinct advantage of the CNN approach over RF and SVM is the ability to simultaneously classify a broad group consisting of several co-occurring species along with more focused, less variable, target species. Our CNN+OBIA approach outperformed RF and SVM methods for classifying the heterogeneous coastal sage scrub group and several individual species.

We focused on creating an effective classification model for the four most dominant shrub and tree species in a dense and heterogeneous shrubland community; a reasonable next step would be to include additional species in the model. Generating a model is simple for locally dominant species because it is easiest to collect the needed training and testing data. Once a robust model is trained, it can be applied to other sites and evaluated with fewer survey points required for validation. Including less common species would require a larger suitable training area reflective of the composition of nearby application sites. The process of target species and training site selection are dependent on expert knowledge of regional plant communities. For example, the variable classification performance in *A. fasciculatum* in Site 2 (Figure A.1 can be explained by the low abundance of *A. fasciculatum*. We were only able to locate nine distinct patches of *A. fasiciculatum* in Site 2 that met our ground survey criteria and six patches with neighboring coastal sage scrub, *A. pumila*, or *C. rigidus* causing a distinct drop in map reliability (recall) for this region. This means that care and creativity are needed when interpreting classification performance for locally rare species.

For example, the poor classification accuracy of *Ceanothus rigidus* provides a good example of what can happen when there are not an adequate number of specimens to adequately train the model and an inadequate number of validation points in application sites. In the case of *C. rigidus* the low number of available training subjects resulted in high recall rates indicating that ground survey points were correctly identified in the map but the low precision and accuracy statistics (F1, Kappa) indicating that the model misclassified other non-target points as C. rigidus. We were able to apply expert knowledge, and trial-and-error, to our classification fuzzy logic schema, setting a high probability threshold for classification of *C. rigidus* (p=0.85) to reduce the prevalence of misclassification, although some misclassification persisted. This misclassification may be rectified by conducting lower elevation flights to gain higher resolution data, conducting surveys across much larger regions to increase the species sample abundance or by timing flights to coincide with the colorful seasonal bloom of *C. rigidus*.

Integrating structural features of the vegetation (i.e., canopy height and slope) with multispectral data into the multiresolution segmentation process was a powerful component in the identification of several species and structural features. For example, *Quercus agrifolia* was usually the tallest species in the landscape and had a consistently hemispherical crown shape that segmented well and helped produce a very high classification accuracy.

Grouping standing deadwood from multiple species into a single category may reduce the deadwood classification accuracy, as different species exhibit variations in dieback patterns and decay processes, which can be overlooked when combined. However, this aggregate approach can be effective at supporting the delineation of bareground, which often has similar spectral properties. In our study, manzanitas (*A. pumila* and *A. tomentosa*), chamise (*A. fasciculatum*), and oak (*Q. agrifolia*) were the predominant species exhibiting deadwood characteristics. In the future, creating separate classifications for each species could enhance classification accuracy and ecological relevance, providing a comprehensive understanding of dieback dynamics in the ecosystem. We attribute the high performance in deadwood detection to the abrupt variation in canopy heights and slope dynamics within manzanita and chamise dieback patches coupled with high NIR and NIR-edge absorption and low red absorption. Although our study does not delineate species-specific deadwood detection, it does offer a suitable alternative to rectifying a challenge with correctly classifying bareground from standing deadwood in forest systems (Zielewska-Büttner et al., 2020).

We explored the use of a CNN+OBIA deep-learning approach to classify vegetation cover at the species level using very high-resolution imagery collected using UAVs. Cover classification at these levels is essential for investigating the distribution and health of ecologically and economically important species in a variety of wildland, urban, and agricultural landscapes. This method holds great promise for supporting conservation management practices in wildland communities where target species may be located in inaccessible areas or distributed over large expanses, especially in heterogeneous wildland communities. The ability to accurately classify standing deadwood and areas of bareground is equally important as it could be used to study patterns of dieback and growth in these communities. A continuing challenge is the difficulty of collecting adequate data to train models for identification of locally rare species. Multi-seasonal flights may capture phenological differences (i.e., flowering) useful for developing robust classification schema. The ease of flight planning and high-resolution sensor capabilities of drones make them well-suited to do this work in the future.

## Data Availability

The data that support the findings of this study are openly available in Dryad at https://doi.org/10.7291/D1KH4K

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# Chapter 3

# Machine Learning vs. Empirical Models: Estimating Leaf Wetness Patterns in a Wildland Landscape for Plant Disease Management

## 3.1 Introduction

Integrated Pest Management (IPM) can reduce risk of plant disease, but requires detailed monitoring of the weather conditions that affect pathogen performance. A critical factor is the duration of liquid water on the surface of plant leaves, which is often a limiting factor in infection by foliar plant pathogens and in production and dispersal of fungal spores (Rowlandson et al., 2015). Leaf wetness data are integrated into models of disease development and into decision support systems that guide growers and land managers in optimized application of chemical treatments or biological management practices (Pitblado, 1992; Narouei-Khandan et al., 2020).

The relationship between leaf wetness conditions and plant disease has been demonstrated across a range of disease-causing fungal and bacterial pathogens in agricultural crops and forest trees (Arauz & Sutton, 1989; Huber & Gillespie, 1992; Lan et al., 2019). Most pathogens require that liquid water persists for several hours on the plant surfaces before they can infect the plant. Free water on leaves from fog, dew, rain, guttation, and sprinklers can promote fungal and bacterial infections and spread (Rowlandson et al., 2015). Higher air temperatures that coincide with extended periods of leaf wetness increase rates of fungal spore germination, infection, and sporulation in several foliar pathogens (Magarey et al., 2005).

In both agricultural and wildland ecosystems, leaf moisture conditions can vary strongly across the landscape, leading to strong spatial patterns in disease pressure (Bradley et al., 2003). Leaf wetness is measured using field-based sensors capable of detecting and recording the duration of leaf wetness. Conventional electronic leaf wetness sensors most often utilize a circuit plate sensor and datalogger capable of recording changes in electrical resistance or capacitance of the sensor surface as water decreases resistance and increases the dielectric constant relative to air (Rowlandson et al., 2015). Leaf wetness sensors are seldom part of standard meteorological monitoring, making access to leaf wetness data difficult for researchers and growers to access (Rowlandson et al., 2015). As a consequence, a variety of empirical and physical models have been developed to predict leaf wetness duration from readily accessible conventional weather station measurements. Empirical models range in complexity from simple threshold models based solely on relative humidity (e.g., Sentelhas et al., 2008; Wichink Kruit et al., 2008) to more complex empirical models that use multiple abiotic factors including air temperature, relative humidity, dew point, wind speed, and solar radiation (Pedro & Gillespie, 1981; Gleason et al., 1994; Kim et al., 2002).

Continued advances in machine learning techniques and high-performance computing have created new opportunities to harness large amounts of available environmental data to better meet critical needs in plant disease management (Liakos et al., 2018). Machine learning (ML) methods are algorithms that are not explicitly programmed for how to solve a specific problem; instead, they become more accurate through iterative training on examples and adjustments to tuning algorithms (Alpaydin, 2020). In this way, computers develop pattern recognition by continuously learning from data through a process of prediction and adjustment, without the need for a pre-programmed solution (Liakos et al., 2018). Several researchers have proposed that machine learning classification methods can provide better predictions of leaf wetness compared to conventional empirical threshold methods (Lee et al., 2016; Shruthi et al., 2019; Asadi & Tian, 2021; Gillespie et al., 2021). However, machine learning approaches have some of the same vulnerabilities as empirical approaches because they depend heavily on the quality, objectivity, and size of training data used to develop models. Most notably, machine learning approaches require large amounts of data that then require energy demanding and expensive computational resources and processing time.

Here we compare the effectiveness of nine popular machine learning algorithms and four simple, conventional empirical threshold models to characterize patterns of leaf wetness across a spatially heterogeneous region of a temperate maritime wildland ecosystem. We identify suitable machine learning algorithms for estimating leaf wetness and propose that the use of simple empirical models based on dew point depression or relative humidity thresholds perform well compared to machine learning techniques. We applied these models across the landscape during the coastal summer fog season when frequent leaf surface wetting and seasonably warm temperatures can create a favorable environment for the development of fungal diseases. Lastly, we relate interpolated leaf wetness duration to patterns of disease-related dieback in two species of endemic manzanita shrubs with differing distributions.

## 3.2 Methods

### Empirical threshold models

Threshold models of leaf wetness are empirical models that define a time period as wet if a meteorological variable (e.g., relative humidity) is greater than a specified value. Several such models are well tested, and we explored the performance of four of these models in our system. Three of the most widely accepted threshold models predicted leaves are wet during periods when relative humidity ($RH$) $> 87\%$ (Wichink Kruit et al., 2008), $> 90\%$ (Gleason et al., 1994) or $RH > 92\%$ (Gillespie et al., 2021).

We implemented three empirical threshold models based on these constant relative humidity threshold (87%, 90%, 92%).

Dew point depression has also been suggested as an estimator of leaf wetness duration (Huber & Gillespie, 1992) as it is known to be a predictor of dew formation on surfaces (Monteith, 1957). Dew point depression (DPD) is the difference between an observed air temperature and the temperature at dew point. Dew point was estimated using the Magnus formula (Sonntag, 1990) and observed air temperature (T) and relative humidity (RH) (Equation 2.1). For the range from –45°C to 60°C, Magnus parameters are $\beta = 17.62$ and $\lambda = 243.12$°C. Gillespie et al. (1993) proposed that the duration of leaf wetness can be estimated as the length of time that DPD remains between two specific limits of 2°C for dew onset and 3.8°C for drying.

$$Dp(T, RH) = \frac{\lambda \cdot \left( ln\left(\frac{RH}{100}\right) + \frac{\beta \cdot T}{\lambda + T} \right)}{\beta - \left( ln\left(\frac{RH}{100}\right) + \frac{\beta \cdot T}{\lambda + T} \right)} \tag{3.1}$$

### Machine Learning Classification

Machine learning methods were selected based on the prevalence of their use in models of leaf wetness and a recent evaluation of the efficacy of these methods reported in Gillespie et al. (2021). The goal of all of the classification modeling approaches was to assess the models' ability to use meteorological data to recognize two classes of leaf wetness: 'Wet' and 'Dry'. Like Gillespie et al. (2021), we evaluated several algorithms used in the modeling of leaf wetness and leaf wetness duration with a mixture of linear (logistic regression (LR) and linear discriminant (LDA)), nonlinear (Gaussian Naïve Bayes (GNB), Classification and Regression Trees (CART), and k-nearest neighbor (kNN)), and more complex methods (Linear Support Vector Machine Classifier (SVM), Random Forest (RF), eXtreme Gradient Boosting (XGB), and Multilevel Perceptron (MLP)). Below is a brief description of each machine learning algorithm.

### Logistic Regression (LR)

Logistic regression is a statistical analysis method used to predict a binary outcome based on explanatory features (Sperandei, 2014). Logistic regression is an important reference model in the discipline of machine learning that is capable of performing similarly to more complex machine learning classification models (Christodoulou et al., 2019). The logistic model fits a sigmoid function to observations and returns a probability that can be used to distinguish between binary categories by using the odds ratio obtained in the presence of explanatory features.

### Linear Discriminant Analysis (LDA)

Linear discriminant analysis uses linear combinations of explanatory features to divide the data space into pre-defined groups. The resulting linear functions can then be used to classify observations into the most likely class. However, the derived linear decision boundaries may not effectively separate classes that are not arranged along linear gradients (A. Sharma & Paliwal, 2015).

### Gaussian Naïve Bayes (GNB)

Naïve Bayes classifiers are a group of supervised learning algorithms based on the application of Bayes' theorem. These approaches find the most probable classification from the available classes, given the features that describe the observation. A central assumption of naïve Bayes methods requires conditional independence between every pair of features given the value of a classification variable. However, for models predicting categorical values, the conditional independence assumption is less restrictive and the resulting predications can have low error rates, even when there are strong attribute dependencies (Domingos & Pazzani, 1997). Additionally, Bayesian optimizers can be used to fine-tune hyperparameters for more complex modeling approaches such as random forest models (Wang et al., 2019; Asadi & Tian, 2021). Hyperparameters are values that control the learning process that the machine learning algorithm uses to determine the values of model parameters. Hyperparameters are set by the researcher and used by the learning algorithm but they are not part of the resulting model.

### Classification and Regression Trees (CART)

Classification and Regression Trees (CART), also known as Decision Trees (DT), are a well-established algorithm for predictive classification modeling of leaf wetness (Gleason et al., 1994; Wang et al., 2019). The process of training a CART model from data involves selecting which input features and thresholds for those features lead to a suitable decision tree model, while minimizing the cost function (complexity) used to choose the split points. A CART model predicts the classification label by evaluating a tree of if-then-else true/false feature questions. This leads to an estimate of the minimum number of questions needed to determine the probability of making a correct decision. The choice of stopping criteria can produce CART models that are highly tuned to the training data, and thus not generally applicable. Pruning methods can be used to produce simplier trees with fewer splits that reduce this problem of overfitting.

### K-nearest neighbor (kNN)

K-nearest neighbor (kNN) classifiers are a statistical approach to machine learning where prediction classifications are made based on majority vote from $k$ neighboring values from an initial cluster of training data with known classifications (Cunningham & Delany, 2021). They are easy to implement and have highly transparent inner workings, and it is easy to understand the output predictions. They are robust to noisy training data, but they can be computationally intensive with lengthy run-times for large datasets; more readily available powerful computational hardware makes run-time performance less of an issue. A persistent issue for kNN model implementation is poor performance in accurately classifying rare events, especially with large-dimensional datasets where less relevant features can amplify inaccurate predictions.

### Support Vector Machine (SVM)

Support Vector Machine classifier algorithms find a hyperplane that creates a classification boundary between data based on explanatory features. These hyperplanes take on a dimensional space equivalent to the number of features used to develop the model. SVM finds the optimal hyperplanes that are relatively close to opposing classes (i.e., wet and dry leaves) and utilizes the neighboring training data to refine the decision boundaries for model classification (Kecman, 2005). SVM classifers perform well when explanatory features create a distinct margin of separation between predicted classes. SVM classifiers are less suitable for large datasets and complex non-linear classfication kernels because of computational time and memory requirements.

### Random Forest (RF)

Random Forest is a machine learning algorithm that utilizes several individual decision trees in an ensemble of decision trees, to create a final classification based on a majority vote for the most probable class. The parameters of a random forest are the variables and thresholds used to split each node learned during training. Each decision tree is constructed based on a random subset of the training dataset to avoid model overfitting. This modeling approach is comparatively slower than a single decision tree approaches (i.e., CART) but the application of hyperparameters in random forests can result in faster and more accurate model response. In the case of a random forest, hyperparameters include the number of decision trees in the forest and the number of features considered by each tree.

### eXtreme Gradient Boosting (XGB)

Extreme Gradient Boosting (XGB) is a decision tree approach built on ensemble learning, combined with gradient boosting, a technique with excellent predictive performance and rapid processing time (Chen & Guestrin, 2016; Solís & Rojas-Herrera, 2021). The ensemble approach of XGB is similar to random forests but differs in how the trees are constructed and combined. Instead of using a bagging approach, XGB models use boosting, which is a method that combines weaker learning decision trees into stronger learning groups by creating sequential models such that the final model has the highest accuracy. These models are built sequentially by minimizing the developing gradient of error from previous models by promoting (i.e., boosting) the influence of higher performing models for each successive prediction.

### Multilayer Perceptron (MLP)

A Multilayer Perceptron (MLP) classifier is a classification modeling approach based on a feedforward artificial neural network that utilizes a supervised training technique called backpropagation. A MLP network is made up of multiple layers of nodes initially designed as a simple algorithm for performing binary classification in the study of biological cognitive systems (Rosenblatt, 1958) and later adapted into fully connected multiple layer perceptron networks that allow the modeling of a feature hierarchy (Baum, 1988). The MLP network starts with an input layer consisting of nodes for each input feature type followed by a fully connected set of one or more hidden layers with no feedback connections that loop model outputs back into prior layers (Taud & Mas, 2018). Each hidden layer is made up of nodes consisting of an identical nonlinear activation function (i.e., logistic) capable of assigning model parameters (i.e., weights and biases) to node connections based on their successful mapping of inputs to outputs (Francl & Panigrahi, 1997). The model training process utilizes backpropagation to assess the magnitude of the difference between the actual output and the estimated output, and the network weights are adjusted to reduce the error (S. Sharma et al., 2017). Nodes in a hidden layer each contain an identical activation function that is used to train the network. Like other machine learning approaches, the fully connected nature of MLP models can result in a considerable total number of parameters (i.e., weights and biases) that can increase computation time. However, MLP's processing speed and accuracy can be improved by tuning a number of hyperparameters (i.e., number of hidden layers, nodes, and learning iterations) and providing adequate training data.

### Research Site

All research occurred on the 246-ha University California Santa Cruz - Fort Ord Natural Reserve (UCSC-FONR) Monterey Bay, CA (Figure 3.1). The UCSC-FONR is located approximately 129 km south of San Francisco, CA and bordered by the city of Marina. The reserve is fragmented by development into a more coastal parcel to the north and a more inland parcel to the south. This reserve serves as an ideal setting for this research given the abundance of low growing shrublands and rolling terrain (96-ha) ranging in elevation between 21m to 58m above mean sea level. Daily ambient air temperatures typically range from 4°C to 21°C, annual average 15°C. Fog occurs often during mornings throughout the year and is more frequent and persistent from summer to early fall (June-September). Average annual rainfall (460 mm / year) occurs almost entirely between October and May.

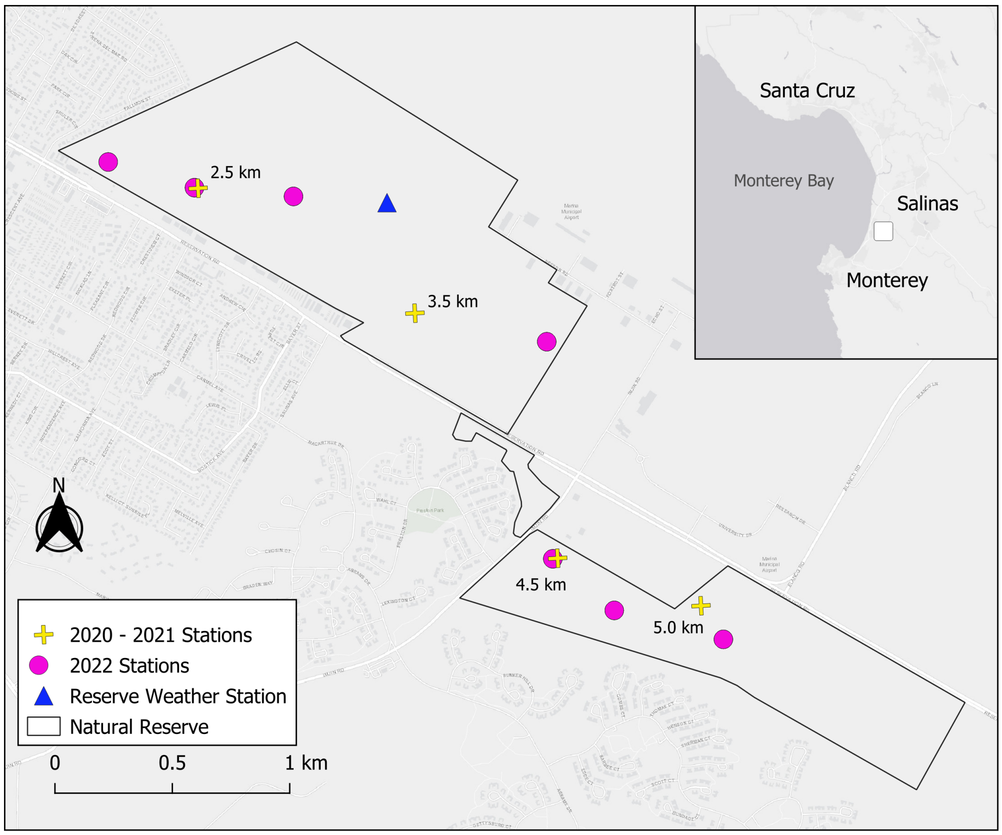


Figure 3.1: Locations of meteorological stations measuring relative humidity, air temperature, and leaf wetness. Stations named from 2020-2021 are named by their distance (km) from the coast. The meteorological station collecting solar radiation and windspeed data is named 'Reserve Weather Station'. The square in the inset map denotes the approximate location of the UCSC Fort Ord Natural Reserve. Backdrop imagery source: World Imagery Esri, Maxar, Earthstar Geographics (2022).

### Meteorological Sensors

In order to measure leaf wetness in relation to air temperature and relative humidity, we installed four Onset Hobo USB Micro Station dataloggers (Model: H21-USB) equipped with Leaf Wetness (Model: S-LWA-M003S-LWA-M003), and Temperature/Relative Humidity (Model: S-THB-M002) sensors set at 1.25m height in similar vegetation clearings along a coastal to inland gradient (Figure 3.1; 2020-21 stations). The sensor stations were positioned away from vegetation obstructions no closer than a distance equal to four times their height. All stations were installed with the leaf wetness sensors positioned on the same north-facing orientation and inclined at 45°. Stations were installed in early February 2020.

The deployed sensors measured surface wetness as a used change in capacitance in response to water accumulation on the sensor surface. The leaf wetness sensor produced an output between 0% and 100% (repeatability ± 5%); the output was converted to a binary variable where values from 0-20% were coded as dry and readings above 20% were coded as wet. The 20% threshold was determined through field calibration during time periods when the wet/dry transition typically occurred. For this field calibration the sensors we temporarily installed all four wetness sensors in the same study area and, while logging data, visually observed the plant species of interest to record the time of day and rate at which the foliage transitions from wet to dry. Wetness readings of 20% or less on the sensor corresponded to leaves that were visibly dry.

Each station underwent routine monthly monitoring and maintenance to reduce prolonged influence of biofouling on measurements. Stations recorded temperature (from 0°C to 50°C, accuracy ± 0.21°C), relative humidity (10% to 90%, accuracy ± 2.5%; below 10% or above 90%, accuracy ± 5%), and leaf wetness in 10-min intervals between February 2020 until March 2022 (Table 2.1). Recurring damage from animal chewing, biofouling, power loss, and vandalism resulted in several incomplete records from two of the stations (Table 2.1, Stations 2.5 and 3.5). Only complete records containing measurements of air temperature, relative humidity, and leaf wetness were used in our analysis.

Solar radiation and windspeed data were acquired from a nearby long-term meteorological station maintained by the UC Natural Reserve System (Figure 2.1; Reserve Met Station). Total solar radiation data was collected with the Li-Cor LI200X Silicon Pyranometer which measures sun plus sky radiation at the 400 - 1100 nm wavelengths using a silicon photovoltaic detector with an absolute error in natural daylight is ± 5% maximum and sensitivity of 0.2 kW $m^{-2}$ m$V^{-1}$. The sensor is calibrated annually against an Eppley precision spectral pyranometer. Windspeed data was acquired using the propeller-type anemometer from RM Young Wind Monitor 05103-L (Campbell Scientific) with an accuracy of 0.3 m$s^{-1}$ and starting threshold at 1.0 m$s^{-1}$. Solar radiation data was only available until November 25, 2021 so records of air temperature, relative humidity, leaf wetness, and wind speed were trimmed to this date. Additionally, start times of the dataloggers varied so all data was trimmed to a start date of February 9, 2020. All incomplete records with missing information between February 9, 2020 and November 25, 2021 were deleted. We preferred deletion instead of imputation to avoid the creation of artificial data for several records at stations that experienced intermittent damage (Table 3.1). Total number of observations at sites (e.g., 2.5 km and 3.5 km) are associated with gaps in data collection (Table 3.1).

Table 3.1: Complete 10-min records from the four Onset® meteorological stations (2/9/2020 – 11/25/2021). The 'Original' column are counts of all complete 10-min records and the 'Trimmed' column are counts of complete records common to all four sites

| Coastal Distance (km) | Original | Trimmed |
|---|---|---|
| 2.5 | 78,286 | 77,932 |
| 3.5 | 92,957 | 78,288 |
| 4.5 | 93,095 | 78,426 |
| 5.0 | 93,095 | 78,426 |

**Meteorological Data for Leaf Wetness Model Application**

In order to apply the leaf wetness models across the entire research site in 2022, we designed and deployed a low-cost solar-recharging Arduino-based meteorological dataloggers. Arduino Uno (ATmega328P microcontroller) dataloggers equipped with a waterproof-housed SHT20 I2C sensor, capable of measuring temperature (from -40°C to 125°C, accuracy ± 0.3°C) and capacitive humidity sensor (0% to 100%, accuracy ± 3%) (SENSIRION, Model: DFROBOT SEN0227) were deployed in the same fashion as the four 2020-21 Onset stations (Figure 3.1; 2022 Stations). Arduino-based stations were programmed using the Arduino 2.0 - Integrated Development Environment (IDE) to record data at 10-min intervals and store data to an SD card module. Originally, ten Arduino stations were installed in June 2021 but wildlife damage and vandalism resulted in intermittent data loss across several stations and the complete destruction of three stations. Ultimately, we were successful in collecting data from seven stations for the 2022 water year (October 1, 2021, to September 30, 2022). Model-estimated leaf wetness was determined using hourly interval air temperature, relative humidity, and dew point depression. All data processing and leaf wetness model application was completed using the R Programming language (R Core Team, 2021) and the tidyverse (Wickham et al., 2019) and caret (Kuhn, 2008) packages.

We focused leaf wetness model application on the 2022 summer season (June - September) characterized by the occurrence of dense fog, low clouds, and overcast conditions that often persist during the morning and early afternoon hours. Fog-induced leaf wetness can have a positive effect on plants by providing moisture during the dry summer season; many coastal species are adapted to rely on fog as a moisture source (Dawson & Goldsmith, 2018). However, prolonged surface leaf wetness can harm plant health, especially by creating a favorable environment for the development fungal diseases. Seasonally fog-induced leaf wetness can increase the risk of foliar disease and related dieback in susceptible plant species.

### Meteorological Data Preparation and Leaf Wetness Modeling

In order to include all four stations (2020-2021) in model development, records that were not present in Site 2.5 km data were deleted from the other three stations (Table 3.1). To ensure that deletion of observations did not alter the coastal to inland climate pattern observed between stations, we evaluated the cumulative number of days when daily mean relative humidity levels were at or above 90% for the four stations with, and without, data deletion (Figure 3.2). We estimated the area under the curve for each time series as the summation of the cumulative number of days when daily mean relative humidity levels were at or above 90%.

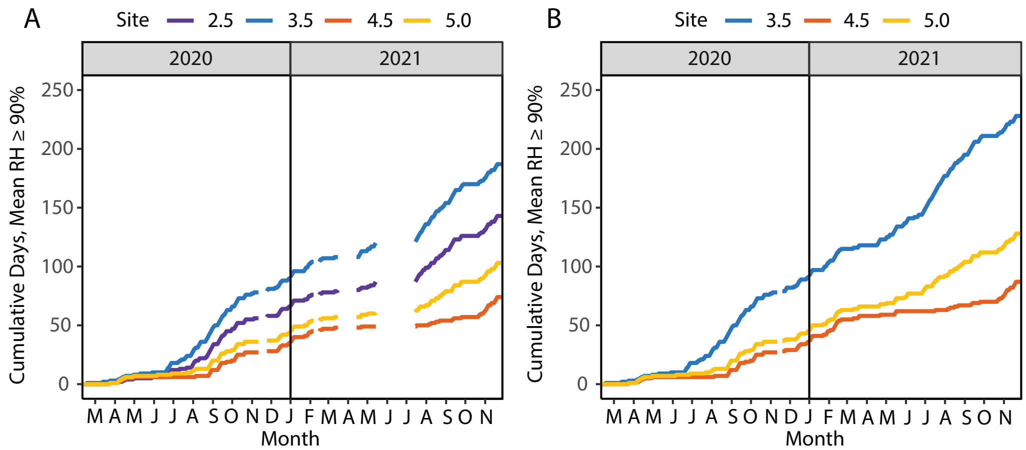


Figure 3.2: Cumulative days with mean $RH \geq 90\%$ for sites 2.5, 3.5, 4.5, 5.0 without a) data trimming and b) with data trimming of sites 3.5, 4.5, and 5.0 based on complete records from Site 2.5.

Data trimming to available records from Site 2.5 reduced AUC values for all three sites but AUC values remained consistent in ranking and retained coastal-to-inland patterns (Table 3.2). We used 2020-2021 data from all four sites in model development with data trimming.

Table 3.2: Area under curve (AUC) calculated as the sum of cumulative days with mean $RH \geq 90\%$. AUCs were calculated only for days with recorded RH values. *AUC Original* summarizes the three sites (3.5, 4.5, 5.0) without data deletion relative to site 2.5 observations. *AUC Trimmed* summarizes all sites with data trimmed to periods observed at site 2.5.

| | AUC | | Proportion | |
|---|---|---|---|---|
| Coastal Distance (km) | Original | Trimmed | Original | Trimmed |
| 2.5 | - | 31,207 | - | - |
| 3.5 | 62,497 | 42,971 | - | - |
| 4.5 | 24,274 | 15,934 | 0.39 | 0.37 |
| 5.0 | 32,874 | 21,677 | 0.53 | 0.50 |

All meteorological data was aggregated into 30-min and hourly interval datasets for model development. Air temperature, relative humidity, dew point depression, wind speed, and total solar radiation data were aggregated as means of 10-min observations. For the 30-min interval, leaf wetness was noted as wet if more than one 10-min record was noted as wet. For the hourly dataset, leaf wetness was noted as wet if 30 minutes or more of the hour were recorded as wet. The empirical 87% relative humidity threshold model outlined in Wichink Kruit et al. (2008) was the only model that utilized 30-min aggregated data. All other models were developed based on hourly aggregated data.

All empirical threshold and machine learning leaf wetness classification models were developed and tested using a script written in the R Programming language (R Core Team, 2021), utilizing machine learning algorithms available in the caret package (Kuhn, 2008). For machine learning classification models, meteorological data was normalized using the preProcess() function with application of the centering and scaling arguments available in the R caret package (Kuhn, 2008; Patro & Sahu, 2015). We used the 2020 data for initial machine learning model development and utilized a repeated k-fold cross validation for training and testing all machine learning models. This process involves splitting the dataset into $k = 3$ parts, training in two parts and testing on the remaining part for all combinations of the train-test splits. This k-folding process was repeated three times for each algorithm with different splits of the data into 3 groups, in an effort to get a more accurate estimate. Models developed from 2020 data were then tested on the 2021 data and a binomial logistic regression was used to 3-fold cross-validate the 2021 model predictions compared to the actual 2021 leaf wetness sensor measurements. For empirical models, predicted leaf wetness values were derived using each threshold model and the 2020 and 2021 data was 3-fold cross-validated to produce multiple replicates of model performance metrics that could be averaged and compared to machine learning model performance.

## Model Metrics

To evaluate empirical and machine learning model performance, we generated a confusion matrix of each model and calculated its accuracy, precision, recall, specificity, sensitivity, F-score, log-loss, and ROC-AUC (Table 3.3). We also computed F-Score (F1) statistics, which provide a metric for evaluating the trade-off between precision and recall as a harmonic mean of the two values (Sundheim, 1992) and can provide a measure of model robustness; a higher F-Score indicates support for predictions made by the model classifier (Fawcett, 2006).

Table 3.3: Model Metrics used to evaluate empirical and machine learning model performance.

| Metric | Equation* | Definition |
|---|---|---|
| Accuracy | $\frac{(TP+TN)}{(TP+TN+FP+FN)}$ | Correct 'Wet' ($TP$) and 'Dry' ($TN$) classifications relative to the total number of event classifications. |
| Precision | $\frac{TP}{(TP+FP)}$ | Correctly classified 'Wet' ($TP$) events relative to the total number of correct and incorrect 'Wet' classifications. |
| Recall (Sensitivity) | $\frac{TP}{(TP+FN)}$ | Correctly classified 'Wet' ($TP$) events relative to the total number of 'Wet' events that were correctly classified as 'Wet' and incorrectly classified as 'Dry'. |
| Specificity | $\frac{TN}{(TN+FP)}$ | Correctly classified 'Dry' events ($TN$) relative to the total number of 'Dry' events that were correctly classified as 'Dry' and incorrectly classified as 'Wet'. |
| F-Score ($F1$) | $2 \times \left(\frac{precision \cdot recall}{precision + recall}\right)$ | Represents the trade-off between precision and recall as a harmonic mean. |

* True Positive ($TP$) = 'Wet' events, correctly classified
True Negative ($TN$) = 'Dry' events, correctly classified
False Positive ($FP$) = 'Dry' events, incorrectly classified as 'Wet',
False Negative ($FN$) = 'Wet' events, incorrectly classified as 'Dry'.

Receiver Operator Characteristic (ROC) curves, and the area under the curve (AUC), describe how consistently a model predicts the positive class ('Wet') when the actual outcome is positive (TP). They provide a metric that summarizes how well a model can distinguish between two target classes ('Wet' or 'Dry') across a variety of thresholds with a focus on describing a model's ability to predict the positive class ('Wet') (Zou et al., 2007). ROC curves illustrate the trade-offs between observed true positive rate (recall) and false positive rate (1-specificity). A 45-degree diagonal across the ROC space defines the baseline (i.e., random classifier) and delineates the least accurate classification predictions possible.

A classifier model that produces a curve closer to the top-left corner in an ROC space indicates perfect classification predictions. All ROC curves presented for machine learning models are represented by a smoothed curve illustrating the predicted probabilities of achieving the correct classification for each year's data. The empirical models in this research are not presented probabilistically and instead represent the observed outcome from the data for each year. The log-loss metric represents the uncertainty of probabilities of a binary outcome for a model by comparing them to actual classifications. This metric is useful for penalizing a classification model that has high confidence about an incorrect classification by providing a summary of how likely the model classified the actual observed set of outcomes was. If a model produces lower prediction probabilities for observations when the actual observation classifications are true (i.e., 1 = 'Wet') the result is a higher log-loss value. A low log-loss represents a low uncertainty of a model but it will tend to favor models that distinguish classes more strongly.

## Model Application

### Estimating Leaf Wetness Across Reserve

Machine learning and empirical models were used to predict summer 2022 hourly categorical leaf wetness using observed air temperature, relative humidity collected by the seven Arduino-based meteorological stations. Data was aggregated by month; cumulative leaf wetness duration, mean air temperature, mean relative humidity, and mean dewpoint depression for each station using the R Programming language (R Core Team, 2021).

We used ordinary kriging to interpolate monthly cumulative leaf wetness duration across the entire research site. In order to evaluate spatial autocorrelation of the data, we fit variogram models to estimate the spatial dependence structure and selected the one that best represents the leaf wetness spatial relationship. The variogram models were used to krig predictions for unobserved locations by considering the values of spatially neighboring observed locations. The weights assigned to these neighboring points depend on their spatial distance and the spatial dependence modeled by the variogram. Kriging interpolation results were evaulated using root mean squared error. We utilized QGIS (version 3.30.1 's-Hertogenbosch) (QGIS Development Team, 2021) and the Smart Map plugin (version 1.3.2) to complete kriging analysis (Pereira et al., 2022).

### Host Species Distribution

To ask whether there was a landscape-level association between leaf wetness duration and plant disease in a wildland community, we used image analysis of drone-based multispectral imagery to measure disease related dieback in two maritime chaparral shrubs. We applied the CNN+OBIA machine learning model developed in Detka et al. (2023) to identify two manazanita shrub species dominating the maritime chaparral regions of the reserve, *Arctostaphylos tomentosa* ssp. *tomentosa* (referred to as *A. tomentosa* throughout this manuscript) and *Arctostaphylos pumila*.

Manzanitas (*Arctostaphylos* spp.) are long-lived evergreen woody shrubs with high species richness and restricted distributions across western North America based on climate, plant communities, and soil types (Vasey and Parker, 2014). Multiple species co-occur in coastal maritime conditions (Parker et al. 2020). In our study system, *Arctostaphylos tomentosa* ssp.*tomentosa* and *Arctostaphylos pumila* are two co-occurring species (Parker et al. 2020) with distinct morphological canopy features that allow them to be distinguished using CNN+OBIA image classification (Detka et al., 2023). Both of these species are locally endemic to the maritime climate regions but vary in their distributions, with *A. pumila* more abundant at the coast and increasing abundance of *A. tomentosa* moving inland. While the ploidy difference between these two taxa does prevent some genetic mixing, field observations suggest that the two species are capable of hybridizing resulting in intermediate leaf characteristics (T. Parker, personal communication, August 11, 2023).

### Assessing Manzanita Canopy Health

In summer 2019, we observed extensive branch canker symptoms in *A. tomentosa* and *A. pumila* species consistent with the fungal pathogen *Neofusicoccum australe* as described by Drake-Schultheis et al (2018) in *A. glauca*. Laboratory experiments have confirmed that disease-related dieback symptoms were caused by *N. australe* (Detka, unpublished).

Manzanita canopy health was classified using a Normalized Difference Vegetation Index (NDVI) generated from multispectral drone imagery (Detka et al., 2023) and compared to ground-based transect surveys. NDVI is a widely used measure for assessing overall plant canopy health remote sensing imagery (Burgan, 1993). The NDVI measurement is based on the principle that the cell structure of healthy leaf tissue has (1) decreased reflectance of red light wavelengths and (2) increased near-infrared reflectance from chlorophyll pigments. Plants that are 'healthy' with high chlorophyll content absorb more incoming red wavelength light and reflect a higher proportion of NIR than 'less healthy' plants. NDVI values are normalized to range from -1 to 1, with positive values indicating more NIR than red reflectance (Equation 2.2). For healthy vegetation, there will be a greater relative absorption of red by chlorophyll compared to NIR, and NDVI values will approach 1. As chlorophyll activity decreases, due to stress or senescence, NDVI approaches 0 due to less absorption of visible red light. NDVI values less than zero typically represent dead vegetation, baregroud, or water bodies.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \tag{3.2}$$

We selected NDVI cutoff values for manzanita canopy gaps and bareground ($NDVI < 0$), unhealthy manzanita canopy ($0 - 0.2$), and healthy live manzanita canopy ($> 0.2$) based on obvious visual condition of vegetation in the field and cross-comparison with RGB and NDVI rasters. These ranges correspond with widely reported values for assessing vegetation cover (DeFries & Townshend, 1994; Al-Doski et al., 2013; de la Iglesia Martinez & Labib, 2023).

To estimate manzanita canopy health from drone imagery, we created a 5-m x 5-m grid overlay for each manzanita species and generated NDVI classification raster zonal statistics for each grid cell. For each grid cell, we calculated the total area of a cell occupied by a species and the percentage of healthy and dieback canopy from NDVI classification rasters. To assess plant health on the ground, we conducted three 30-m line intercept transects at four locations through the reserve, for a total of twelve transects (Figure 3.3). Transects were placed haphazardly in areas dominated by manzanita cover in orientations that included cover of both species. Start points and headings were randomized as much as possible while also avoiding hazards (i.e., large areas of poison oak) or sensitive woodrat middens. Woody plant canopy cover was recorded as the length (m) intercepted by each species along 30-m ground transects. For the two target manzanita species, we noted the general condition (Live/Dead), presence of disease and pest symptoms, and the dominant coloration of live (green) and diseased dieback (grey, brown) symptoms for transect segments longer than 10cm. Canopy gaps and open patches larger than 10cm were recorded as bareground, standing deadwood, and leaf litter (duff). Ground estimates of percent canopy dieback were calculated for each manzanita species by dividing the intercepted lengths (m) of dieback by the total species cover. Linear regression was used to evaluate association between canopy dieback, coastal distance, and leaf wetness duration.

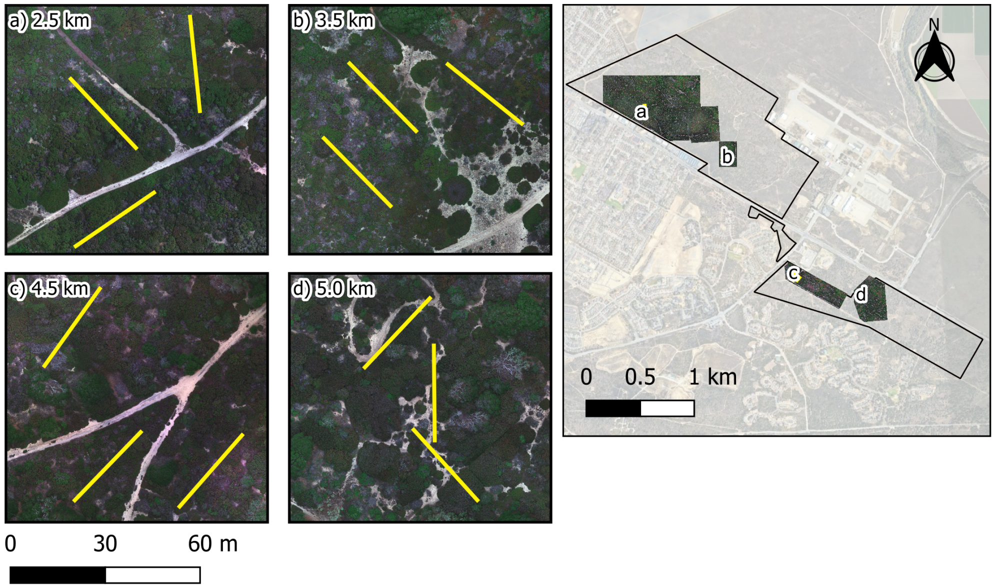


Figure 3.3: Ground survey sites (a-d) and 30m transect locations (yellow lines). Black border outlines UCSC Fort Ord Natural Reserve. Backdrop imagery source: World Imagery Esri, Maxar, Earthstar Geographics (2022). Research site imagery is displayed as RGB orthomosaic from UAV research flights.

## 3.3 Results

### Input feature associations with leaf wetness

Correlations among observed input features and leaf wetness events for the entire dataset confirms several associations expected based on prior knowledge of micrometerological principles (Figure 3.4). Air temperature, dew point depression, wind speed, and solar radiation were all negatively correlated with leaf wetness events. Dewpoint depression had the strongest negative correlation with leaf wetness events (Pearson's R = -0.63) followed by solar radiation (Pearson's R = -0.59), air temperature (Pearson's R = -0.55), and wind speed (Pearson's R = -0.51). Relative humidity had a strong positive association with leaf wetness events (Pearson's R = 0.72) and was negatively correlated with other input features indicating multicollinearity. Dew point depression is defined by the relationship between air temperature and relative humidity, which explains observed collinearity patterns between dew point depression and these variables. Correlation associations support that cloudy skies, cool moist air, and light winds are associated with leaf wetting.

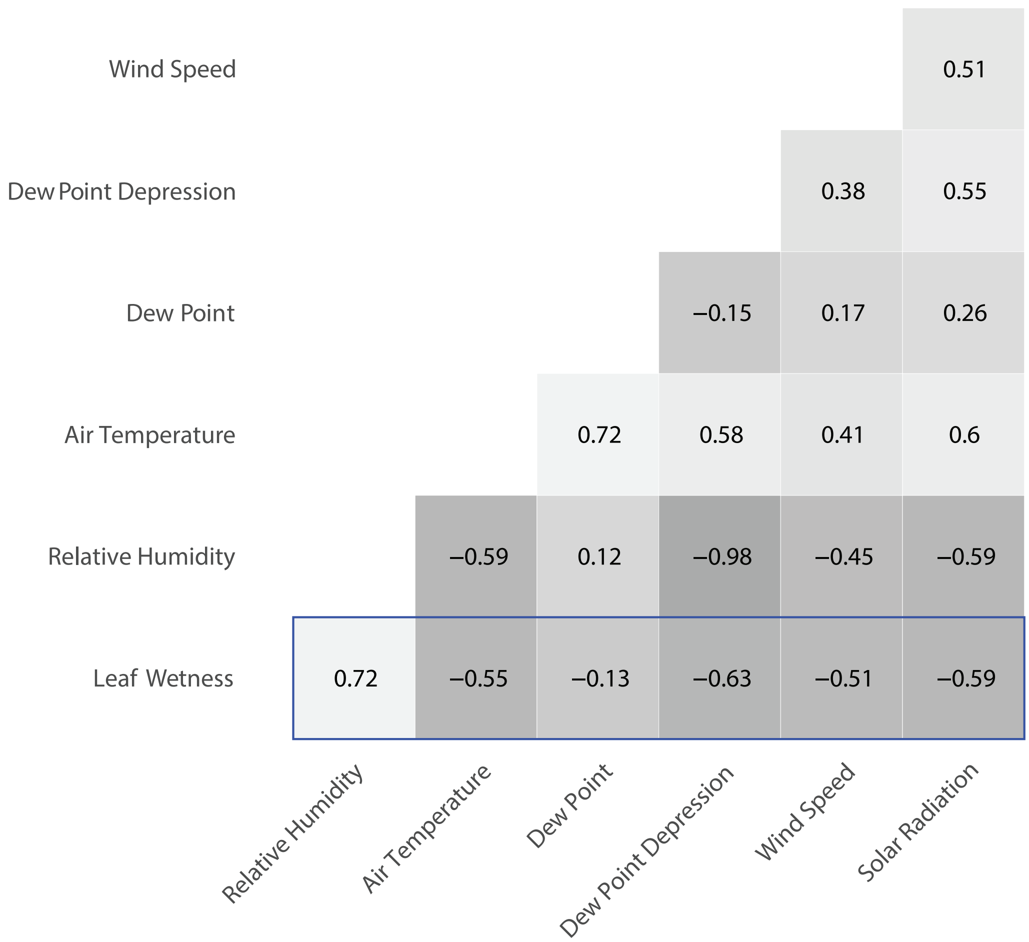


Figure 3.4: Pearson Correlation heatmap between input features (horizontal axis) and leaf wetness (blue box). Correlation is based 2020 and 2021 data.

### Input Feature Importance

We utilized variable importance evaluation functions to estimate the contribution of each input feature to the machine learning models. ROC curve analysis was conducted on each of the normalized input features and a series of cutoffs were applied to the feature data to predict the classification. The sensitivity and specificity were computed for each cutoff and the ROC curve was computed for individual features. The trapezoidal rule was used to compute the area under the variable importance ROC curve (ROC-AUC) with values closer to 1 representing a greater influence on model classification predictions (Table 2.4). ROC-AUC results support Pearson correlation patterns and confirm that relative humidity and dew point depression are the most influential variables in the machine learning models (Table 2.4).

Table 3.4: Individual input feature variable importance ROC-AUC statistics

| Input Feature | ROC-AUC |
|---|---|
| Dew Point Depression | 0.95 |
| Relative Humidity | 0.95 |
| Air Temperature | 0.83 |
| Solar Radiation | 0.82 |
| Wind Speed | 0.79 |

### Empirical Model Performance

For 2021, the $RH > 87\%$ model tended to overestimate 'Wet' events. The $RH > 87\%$ model had the highest true positive rate (0.95) (Table 2.5, Recall; Figure 2.5a, y-axis) - the probability that an actual 'Wet' observation will correctly classify as 'Wet'. However, the $RH > 87\%$ model also had the highest false positive rate, with the highest probability of mis-classifying 'Dry' observations as 'Wet' (0.26) (Table 2.5, 1-Specificity; Figure 2.5a, x-axis). In contrast, the $RH > 92\%$ model provided the most conservative model 'Wet' classification predictions with the lowest true positive rate (0.81) and lowest false positive rates (0.07).

Dew point depression (DPD) and $RH > 90\%$ model predictions of leaf wetness outperformed $RH > 87\%$ and $RH > 92\%$ models in 2021 (Table 2.5, Figure 2.4a). The $RH > 90\%$ and DPD models had less than a 1% difference in accuracy. However, the $RH > 90\%$ models had a 5% lower true positive rate (recall) for 2021. The $RH > 90\%$ models tend to underestimate wetness, classifying 5% fewer observations as 'Wet' (TP) relative to the number of all observations that should have been identified as 'Wet'. What the $RH > 90\%$ models lack in recall was not made up for in precision. The $RH > 90\%$ models' precision was only 3% better than the DPD models at correctly classified 'Wet' (TP) predictions relative to the total number of 'Wet' predictions – including incorrect wet predictions (FP). The DPD model also has a similar F-Score metric, log loss metric, and AUC score compared to the $RH > 90\%$ model, indicating that the 2021 DPD model is a robust, yet only marginally better empirical models to the $RH > 90\%$ models for predicting leaf wetness. We selected the DPD model as the best performing empirical model and designated it as a reference for the evaluation of machine learning model performance.

### Machine Learning Model Performance

We evaluated the performance of machine learning models on 2021 test data and compared them to the highest performing empirical model (i.e., DPD) (Figures 2.5b-2.5f and Table 2.5). The full-featured model based on relative humidity, air temperature, dew point depression, wind speed, and total solar radiation resulted in at most a 2% increase in accuracy over the empirical dew point depression model. The performance of the machine learning dew point depression models was not significantly different than that of the empirical dew point depression model. ML models based on further reductions in the number of input features performed similarly to empirical threshold models based on relative humidity or dew point depression.

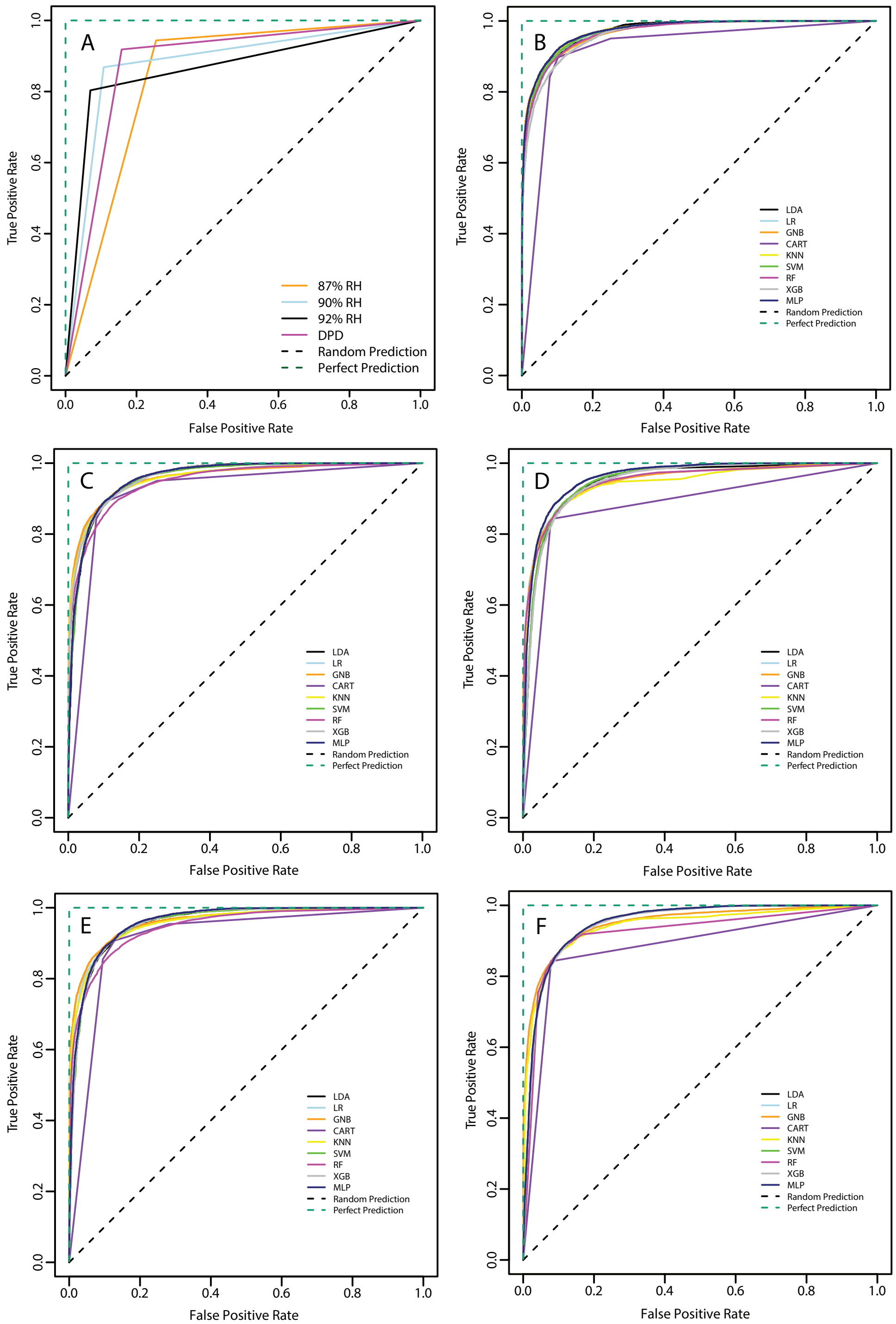


Figure 3.5: 2021 ROC-AUC plots for: A) Empirical B) RH + Air Temp + DPD + Wind Speed + Solar Radiation C) RH + Air Temperature + DPD D) RH + Air Temp E) RH + DPD F) DPD. ROC curves represent predicted probabilities of achieving the correct classification. See Table 2.5 for corresponding AUC metrics.

Table 3.5: Empirical and Machine Learning Model Performance (2021)

| Models[a,b] | Accuracy[c] | Precision | Recall | Specificity | F1 | LogLoss | AUC |
|---|---|---|---|---|---|---|---|
| Empirical Threshold Models | | | | | | | |
| RH > 87 | 85.25 (84.95 - 85.55) *** | 0.81 (0.003) | 0.95 (0.002) | 0.74 (0.005) | 0.87 (0.002) | 0.40 (0.005) | 0.85 (0.003) |
| RH > 90 | 88.13 (87.91 - 88.35) | 0.90 (0.003) | 0.87 (0.002) | 0.89 (0.004) | 0.89 (0.002) | 0.36 (0.004) | 0.88 (0.002) |
| RH > 92 | 86.37 (86.05 - 86.69) *** | 0.93 (0.004) | 0.81 (0.005) | 0.93 (0.004) | 0.87 (0.003) | 0.38 (0.006) | 0.87 (0.003) |
| **DPD** | **88.50 (88.26 - 88.74)** | 0.87 (0.003) | 0.92 (0.003) | 0.84 (0.004) | 0.90 (0.002) | 0.36 (0.004) | 0.88 (0.002) |
| Relative Humidity + Air Temperature + Dew Point Depression + Wind Speed + Total Solar Radiation | | | | | | | |
| LDA | 90.11 (89.81 - 90.41) *** | 0.90 (0.003) | 0.92 (0.003) | 0.88 (0.004) | 0.91 (0.002) | 0.32 (0.006) | 0.90 (0.003) |
| LR | 90.23 (90.00 - 90.46) *** | 0.89 (0.002) | 0.93 (0.002) | 0.87 (0.003) | 0.91 (0.002) | 0.32 (0.004) | 0.90 (0.002) |
| GNB | 89.16 (88.96 - 89.36) ** | 0.87 (0.005) | 0.93 (0.005) | 0.84 (0.008) | 0.90 (0.001) | 0.34 (0.003) | 0.89 (0.002) |
| CART | 89.77 (89.48 - 90.06) ** | 0.91 (0.002) | 0.90 (0.004) | 0.90 (0.003) | 0.90 (0.002) | 0.33 (0.005) | 0.90 (0.002) |
| KNN | 90.62 (90.28 - 90.96) *** | 0.90 (0.004) | 0.92 (0.003) | 0.88 (0.005) | 0.91 (0.003) | 0.31 (0.007) | 0.90 (0.003) |
| SVM | 89.84 (89.54 - 90.14) ** | 0.89 (0.005) | 0.93 (0.005) | 0.87 (0.006) | 0.91 (0.002) | 0.33 (0.006) | 0.90 (0.003) |
| RF | 89.91 (89.57 - 90.25) ** | 0.91 (0.004) | 0.90 (0.003) | 0.90 (0.005) | 0.91 (0.003) | 0.33 (0.007) | 0.90 (0.003) |

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| Models[a,b] | Accuracy[c] | Precision | Recall | Specificity | F1 | LogLoss | AUC |
|---|---|---|---|---|---|---|---|
| XGB | 88.87 (88.47 - 89.27) | 0.91 (0.004) | 0.88 (0.004) | 0.90 (0.005) | 0.90 (0.003) | 0.35 (0.007) | 0.89 (0.004) |
| MLP | 89.48 (89.14 - 89.82) ** | 0.95 (0.004) | 0.85 (0.004) | 0.95 (0.005) | 0.90 (0.003) | 0.32 (0.007) | 0.90 (0.003) |
| Relative Humidity + Air Temperature + Dew Point Depression | | | | | | | |
| LDA | 88.28 (87.93 - 88.63) | 0.88 (0.004) | 0.91 (0.003) | 0.86 (0.006) | 0.89 (0.003) | 0.36 (0.006) | 0.88 (0.003) |
| LR | 89.44 (89.19 - 89.69) ** | 0.89 (0.003) | 0.92 (0.003) | 0.87 (0.004) | 0.90 (0.002) | 0.34 (0.005) | 0.89 (0.002) |
| GNB | 89.53 (89.17 - 89.89) ** | 0.89 (0.003) | 0.93 (0.004) | 0.86 (0.004) | 0.91 (0.003) | 0.33 (0.007) | 0.89 (0.003) |
| CART | 89.28 (88.84 - 89.72) * | 0.91 (0.004) | 0.89 (0.005) | 0.89 (0.005) | 0.90 (0.004) | 0.34 (0.008) | 0.89 (0.004) |
| KNN | 89.18 (88.76 - 89.60) * | 0.90 (0.005) | 0.90 (0.003) | 0.88 (0.006) | 0.90 (0.003) | 0.34 (0.008) | 0.89 (0.004) |
| SVM | 89.32 (89.01 - 89.63) * | 0.89 (0.003) | 0.92 (0.003) | 0.86 (0.003) | 0.90 (0.003) | 0.34 (0.006) | 0.89 (0.003) |
| RF | 87.80 (87.46 - 88.14) | 0.88 (0.005) | 0.89 (0.003) | 0.86 (0.006) | 0.89 (0.003) | 0.37 (0.006) | 0.88 (0.003) |
| XGB | 88.48 (88.10 - 88.86) | 0.89 (0.005) | 0.90 (0.003) | 0.87 (0.007) | 0.89 (0.003) | 0.36 (0.007) | 0.88 (0.004) |
| MLP | 89.17 (88.80 - 89.54) * | 0.92 (0.005) | 0.88 (0.003) | 0.91 (0.006) | 0.90 (0.003) | 0.34 (0.007) | 0.89 (0.003) |
| Relative Humidity + Air Temperature | | | | | | | |
| LDA | 88.68 (88.44 - 88.92) | 0.87 (0.004) | 0.92 (0.004) | 0.85 (0.006) | 0.90 (0.002) | 0.35 (0.004) | 0.88 (0.002) |
| LR | 88.91 (88.76 - 89.06) * | 0.88 (0.004) | 0.92 (0.004) | 0.86 (0.005) | 0.90 (0.001) | 0.35 (0.003) | 0.89 (0.001) |
| GNB | 89.09 (88.87 - 89.31) * | 0.87 (0.005) | 0.94 (0.004) | 0.84 (0.008) | 0.90 (0.001) | 0.34 (0.003) | 0.89 (0.002) |

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| Models[a,b] | Accuracy[c] | Precision | Recall | Specificity | F1 | LogLoss | AUC |
|---|---|---|---|---|---|---|---|
| CART | 88.24 (87.97 - 88.51) | 0.90 (0.004) | 0.87 (0.004) | 0.90 (0.004) | 0.89 (0.002) | 0.36 (0.005) | 0.88 (0.002) |
| KNN | 88.40 (88.19 - 88.61) | 0.89 (0.003) | 0.90 (0.005) | 0.87 (0.005) | 0.89 (0.002) | 0.36 (0.004) | 0.88 (0.002) |
| SVM | 88.85 (88.67 - 89.03) * | 0.88 (0.003) | 0.92 (0.004) | 0.86 (0.005) | 0.90 (0.001) | 0.35 (0.003) | 0.89 (0.002) |
| RF | 86.97 (86.68 - 87.26) | 0.87 (0.004) | 0.88 (0.006) | 0.85 (0.005) | 0.88 (0.003) | 0.39 (0.005) | 0.87 (0.003) |
| XGB | 88.62 (88.29 - 88.95) | 0.88 (0.005) | 0.90 (0.006) | 0.87 (0.006) | 0.89 (0.003) | 0.35 (0.006) | 0.89 (0.003) |
| MLP | 88.81 (88.60 - 89.02) * | 0.88 (0.003) | 0.91 (0.004) | 0.87 (0.004) | 0.90 (0.002) | 0.35 (0.004) | 0.89 (0.002) |
| Relative Humidity + Dew Point Depression | | | | | | | |
| LDA | 88.68 (88.43 - 88.93) | 0.87 (0.005) | 0.90 (0.005) | 0.87 (0.006) | 0.89 (0.002) | 0.34 (0.007) | 0.95 (0.001) |
| LR | 88.64 (88.39 - 88.89) | 0.86 (0.005) | 0.92 (0.005) | 0.86 (0.006) | 0.89 (0.002) | 0.28 (0.004) | 0.95 (0.001) |
| GNB | 88.61 (88.34 - 88.88) | 0.87 (0.006) | 0.90 (0.006) | 0.87 (0.007) | 0.88 (0.002) | 0.34 (0.008) | 0.95 (0.001) |
| CART | 88.79 (88.52 - 89.06) | 0.88 (0.007) | 0.89 (0.007) | 0.88 (0.008) | 0.88 (0.002) | 0.30 (0.012) | 0.93 (0.009) |
| KNN | 88.85 (88.50 - 89.20) | 0.88 (0.004) | 0.89 (0.007) | 0.88 (0.005) | 0.89 (0.003) | 0.51 (0.118) | 0.95 (0.004) |
| SVM | 88.63 (88.38 - 88.88) | 0.86 (0.005) | 0.92 (0.005) | 0.86 (0.006) | 0.89 (0.002) | 0.28 (0.005) | 0.95 (0.001) |
| RF | 88.24 (88.01 - 88.47) | 0.87 (0.006) | 0.89 (0.006) | 0.88 (0.008) | 0.88 (0.002) | 0.78 (0.032) | 0.95 (0.001) |
| XGB | 88.29 (87.99 - 88.59) | 0.87 (0.006) | 0.89 (0.006) | 0.87 (0.007) | 0.88 (0.003) | 0.28 (0.006) | 0.95 (0.002) |
| MLP | 88.65 (88.35 - 88.95) | 0.87 (0.018) | 0.90 (0.028) | 0.88 (0.024) | 0.88 (0.005) | 0.28 (0.005) | 0.96 (0.001) |

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| Models[a,b] | Accuracy[c] | Precision | Recall | Specificity | F1 | LogLoss | AUC |
|---|---|---|---|---|---|---|---|
| Dew Point Depression | | | | | | | |
| LDA | 88.50 (88.19 - 88.81) | 0.88 (0.003) | 0.91 (0.003) | 0.85 (0.004) | 0.90 (0.002) | 0.36 (0.006) | 0.88 (0.003) |
| LR | 88.47 (88.22 - 88.72) | 0.87 (0.003) | 0.92 (0.003) | 0.84 (0.004) | 0.90 (0.002) | 0.36 (0.005) | 0.88 (0.002) |
| GNB | 88.47 (88.08 - 88.86) | 0.89 (0.004) | 0.90 (0.003) | 0.86 (0.004) | 0.89 (0.003) | 0.36 (0.007) | 0.88 (0.004) |
| CART | 88.50 (88.26 - 88.74) | 0.87 (0.003) | 0.92 (0.003) | 0.84 (0.004) | 0.90 (0.002) | 0.36 (0.004) | 0.88 (0.002) |
| KNN | 88.25 (87.94 - 88.56) | 0.89 (0.004) | 0.89 (0.002) | 0.87 (0.005) | 0.89 (0.002) | 0.36 (0.006) | 0.88 (0.003) |
| SVM | 88.47 (88.22 - 88.72) | 0.87 (0.003) | 0.92 (0.003) | 0.84 (0.004) | 0.90 (0.002) | 0.36 (0.005) | 0.88 (0.002) |
| RF | 88.50 (88.12 - 88.88) | 0.89 (0.004) | 0.90 (0.004) | 0.87 (0.005) | 0.89 (0.003) | 0.36 (0.007) | 0.88 (0.003) |
| XGB | 88.52 (88.17 - 88.80) | 0.89 (0.003) | 0.90 (0.004) | 0.86 (0.004) | 0.89 (0.003) | 0.36 (0.006) | 0.88 (0.003) |
| MLP | 88.28 (88.05 - 88.51) | 0.91 (0.004) | 0.87 (0.003) | 0.90 (0.005) | 0.89 (0.002) | 0.36 (0.004) | 0.88 (0.002) |

[a] $RH > 87$ model used aggregated 30-minute datasets; $N_{2020} = 60,230, N_{2021} = 44,156$. All other empirical models (i.e., RH>90, RH>92, DPD) and machine learning models used aggregated hourly datasets; $N_{2020} = 30,116, N_{2021} = 22,091$.

[b] LDA, Linear Discriminant Analysis; LR, Logistic Regression; GNB, Gaussian Naïve Bayes; CART, Classification And Regression Trees; KNN, K-Nearest Neighbors; SVM, Support Vector Machine; RF, Random Forest; XGB, Extreme Gradient Boosting; MLP, Multi-Layer Perceptron.

[c] Denotes model accuracy significantly less than preferred empirical model (bold) based on results of one sample t-tests. ($p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *, $p < 0.1$ +, 0.1 - 1.0 = no symbol). Accuracy values are presented as means and 95% confidence interval. All other parenthetical values are standard deviations.

We used a model-based approach to reassess variable importance since it is more closely tied to the actual model performance and it is able to incorporate the correlation structure between the predictors into the importance calculation regardless of how the importance is calculated. For most of the machine learning classification models, each input feature generates a separate variable importance value for the positive class (i.e., ‘Wet’). These methods are not readily available for naïve Bayes, or kNN modeling approaches (Olden & Jackson, 2002). Results support that RH and DPD were the most important variable to leaf wetness models (Table 2.6).

Table 3.6: Individual input feature variable importance ROC-AUC statistics for machine learning models

| Model | Variable | LDA | LR | CART | SVM | RF | XGP | MLP | Mean |
|---|---|---|---|---|---|---|---|---|---|
| Full Model | Dew Point Depression | 1 | 0.53 | 1 | 1 | 0.82 | 1 | 0.41 | 0.82 (0.25) |
| | Relative Humidity | 0.07 | 1 | 0.99 | 0.99 | 1 | 0.07 | 0.2 | 0.62 (0.47) |
| | Air Temperature | 0.02 | 0.31 | 0.6 | 0.23 | 0.54 | 0.03 | 0.23 | 0.28 (0.23) |
| | Solar Radiation | 0.17 | 0.45 | 0.11 | 0.2 | 0.04 | 0.02 | 0.1 | 0.16 (0.14) |
| $RH + Temp + DPD$ | Relative Humidity | 0 | 1 | 0.97 | 0.99 | 1 | 0.4 | 0.27 | 0.66 (0.43) |
| | Air Temperature | 0.04 | 0.19 | 0 | 0 | 0 | 0 | 0.35 | 0.08 (0.14) |
| | Dew Point Depression | 1 | 0 | 1 | 1 | 0.82 | 1 | 0.38 | 0.74 (0.40) |
| $RH + Temp$ | Relative Humidity | 1 | 1 | 1 | 1 | 1 | 1 | 0.51 | 0.93 (0.19) |
| | AirTemp | 0 | 0 | 0 | 0 | 0 | 0 | 0.49 | 0.07 (0.19) |
| $RH + DPD$ | RH | 0 | 0 | 0 | 0 | 1 | 0 | 0.58 | 0.23 (0.40) |
| | DPD | 1 | 1 | 1 | 1 | 0 | 1 | 0.42 | 0.77 (0.40) |

We selected the MLP machine learning model based on relative humidity and dew point depression for application to 2022 data (Figure 2.5(E) and Table 2.5 $(RH + DPD)$). The MLP approach produced the highest AUC scores and a good balance between precision and recall (Table 2.5). Evaluation of variable importance for the MLP model suggests that relative humidity and dew point depression both contribute to model performance, with relative humidity having more influence on leaf wetness prediction (Table 2.6). Additionally, MLP computational processing time was much shorter (  10 min) compared to some modeling approaches using the same variables (e.g., kNN, SVM; $>$ 1.5 hrs).

### Landscape-level Leaf Wetness Model Application

Kriging analysis was conducted on monthly mean air temperature and relative humidity data across the reserve. Results indicate a summer seasonal pattern with lower mean air temperature (1-2°C) and higher mean relative humidity (5-6%) observed at the coast (Figure 3.6). Additionally, krig interpolation estimates were used to determine the monthly cumulative duration of leaf wetness (Figure 3.7) and confirm that the longest cumulative leaf wetness duration occur during July and August. Both the DPD and MLP models indicate that the coastal regions experience longer duration leaf wetness. This disparity is particularly pronounced in September, where the monthly cumulative leaf wetness duration can differ by as much as 100 hours (Figure 3.7).

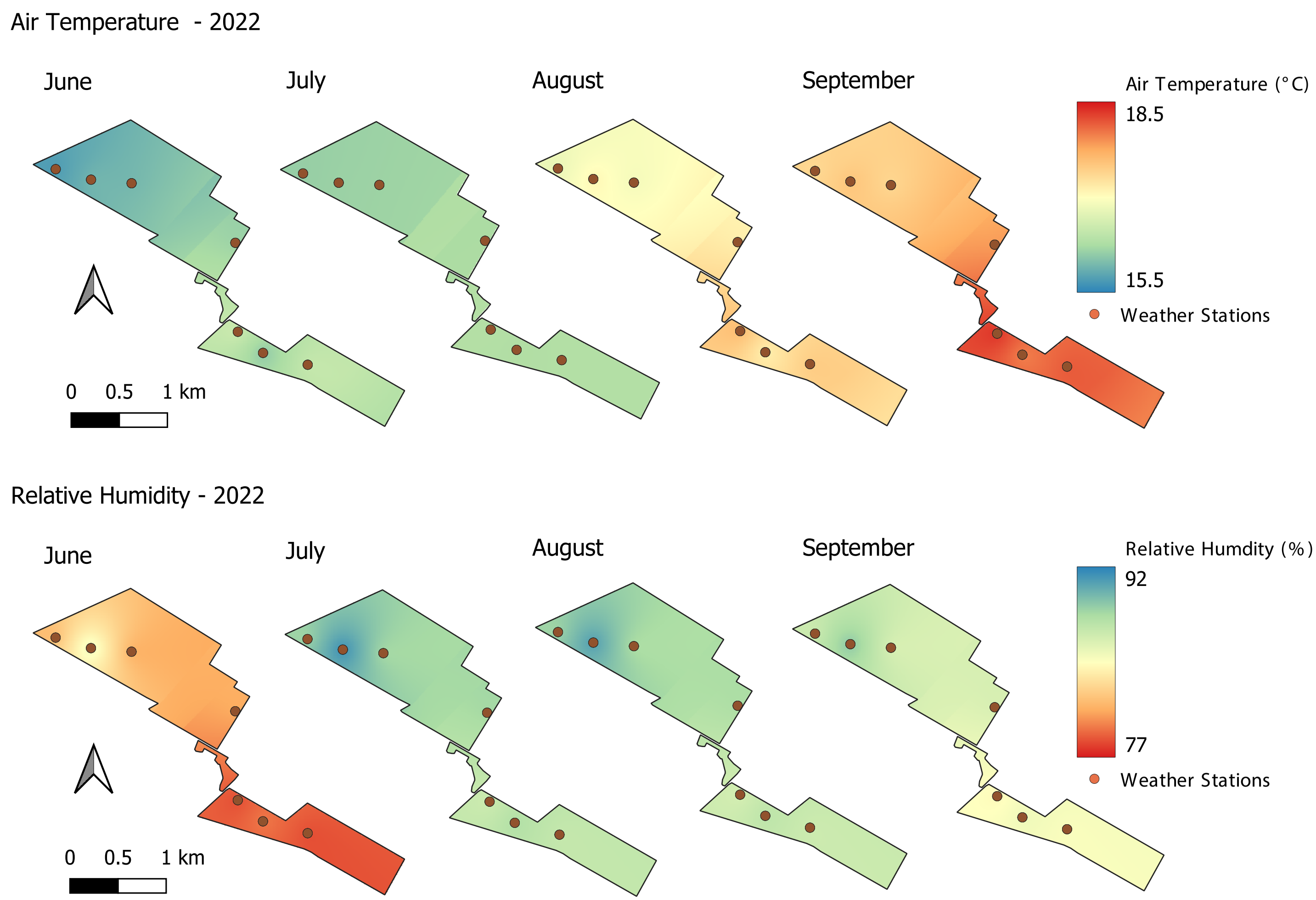


Figure 3.6: Krig estimates of monthly mean air temperature and relative humidity (Summer 2022)

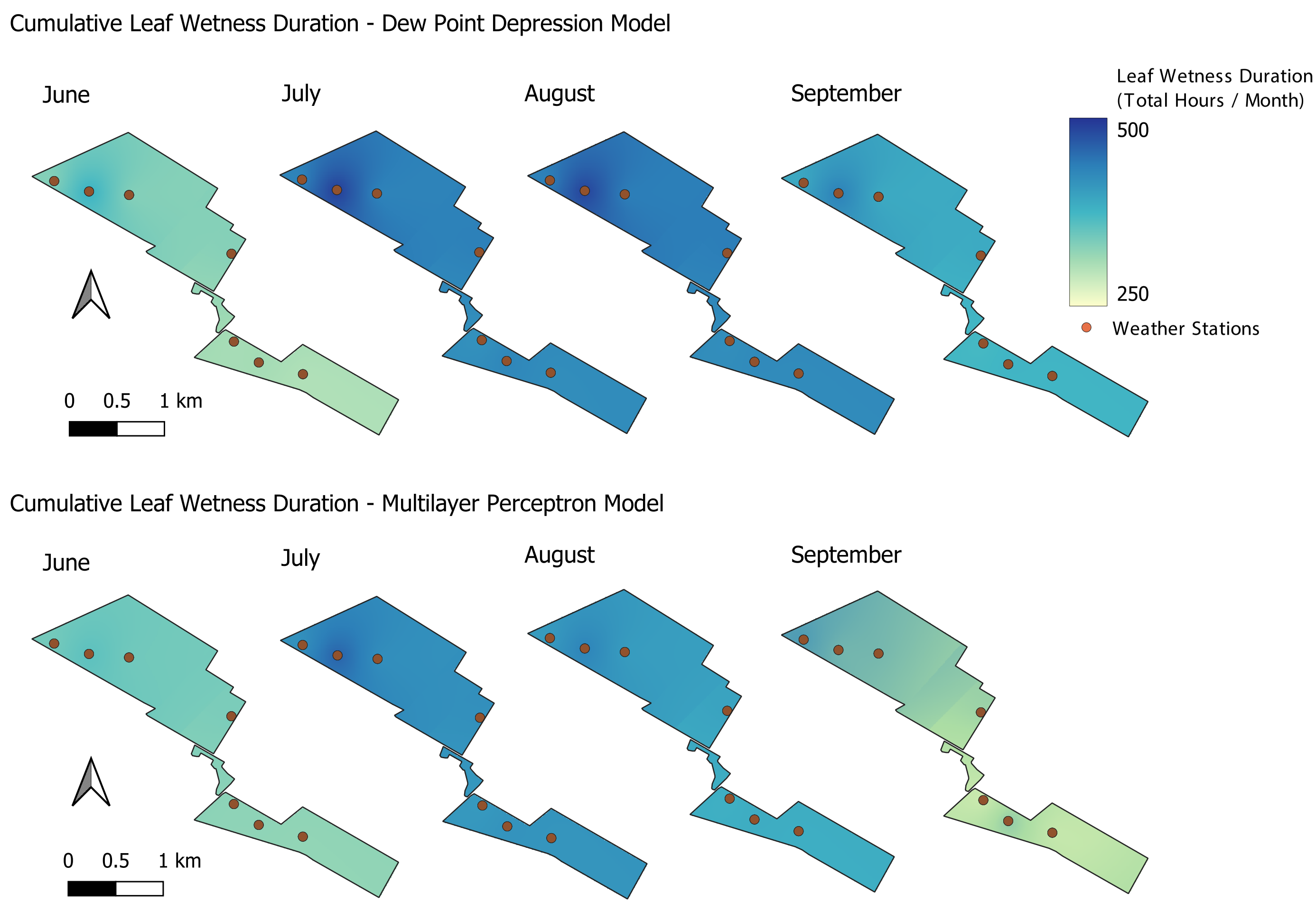


Figure 3.7: Krig estimates of monthly cumulative leaf wetness duration (Summer 2022).

### Manzanita Canopy Health

Overall, analysis of drone-imagery supports that disease-related dieback is more extensive in *A. tomentosa*. Imagery analysis estimated a total of 11.5 ha of identified *A. pumila*, with an estimated 9.0 ha live canopy cover and 2.5 ha dieback cover (21.7% dieback). A total of 13.4 hectares *A. tomentosa* was identified, with an estimated 7.8 ha live canopy cover and 5.6 ha dieback (41.8%).

Canopy dieback estimates obtained from ground transects are consistent with the estimates obtained from drone aerial surveys for both manzanita species. For *A. pumila*, no discernible pattern in canopy dieback was observed in ground or aerial surveys (Figure 3.8 a and c; Figure 3.9 a and c). However, for *A. tomentosa*, the percent canopy dieback was found to be highest at coastal sites and decreased as the distance from the coast increased (Figure 3.8 b and d; Figure 3.8 b and d).

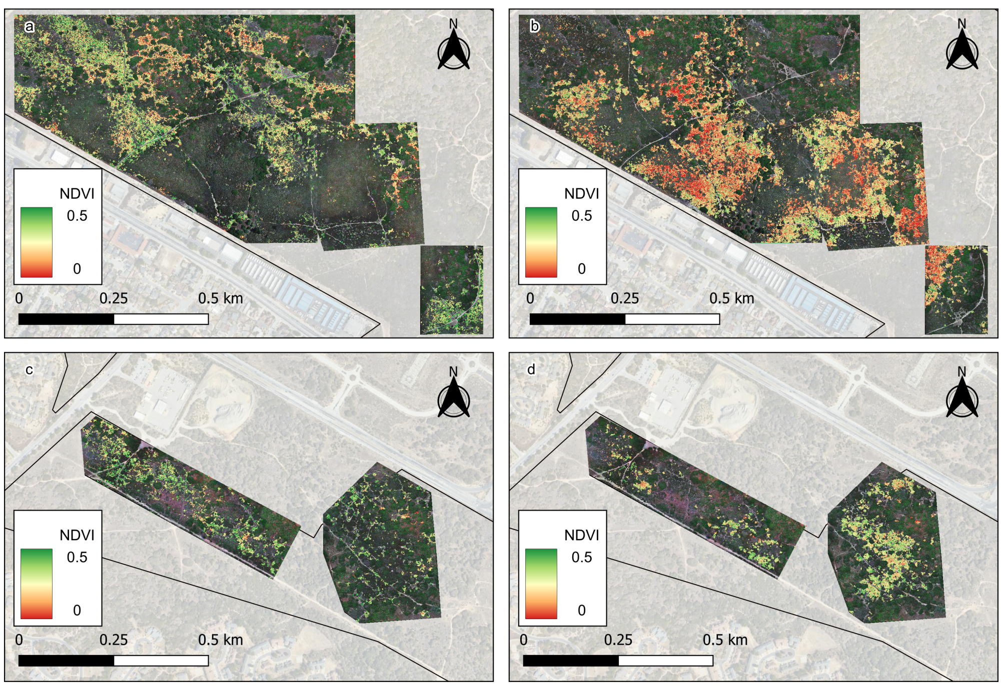


Figure 3.8: Normalized Difference Vegetation Indice (NDVI) values for *A. pumila* (a and c) and *A. tomentosa* (b and d) in North Reserve (top) and South Reserve (bottom). Backdrop imagery source: World Imagery Esri, Maxar, Earthstar Geographics (2022). Research site imagery is displayed as RGB orthomosaic from UAV research flights.

Analysis of all 5-m x 5-m grid cells in the reserve containing *A. tomentosa*

($n = 14,690$) and *A. tomentosa* ($n = 15,098$) supports that the is a stronger association between leaf wetness duration and the extent of canopy dieback for *A. tomentosa* compared to *A. pumila*. Increasing leaf wetness is associated with increased percentages of disease-related canopy dieback in *A. tomentosa* (Figure 3.10).

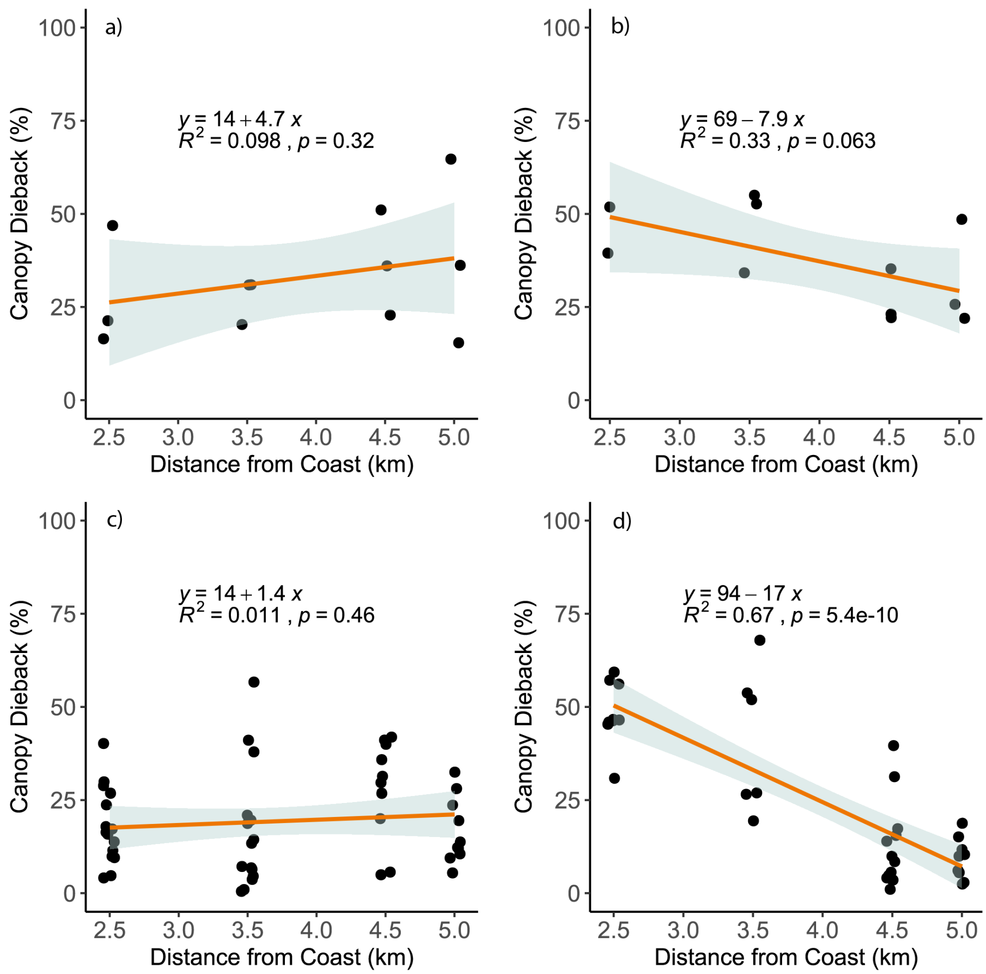


Figure 3.9: Percent area canopy dieback by manzanita species and distance from coast. Ground transect results for a) *A. pumila* and b) *A. tomentosa*. Drone imagery results for c) *A. pumila* and d) *A. tomentosa*.

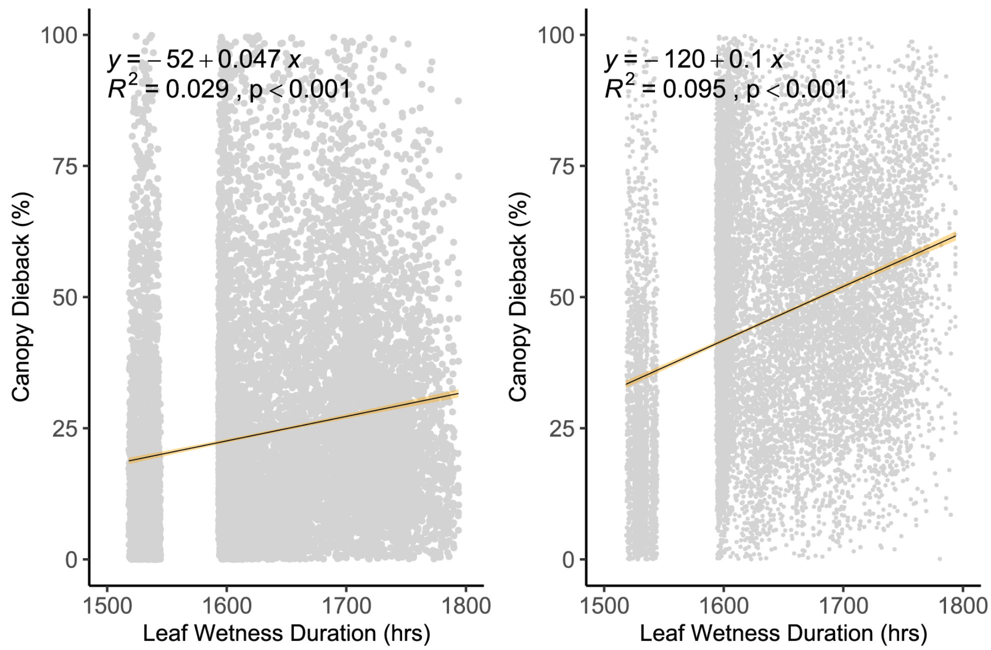


Figure 3.10: Percentage canopy dieback and leaf wetness duration for *A. pumila* (left) and *A. tomentosa* (right). Each dot represents canopy dieback estimated from percentage dieback in each 5-m x 5-m grid and krig cumulative leaf wetness duration at each location. Backdrop imagery source: World Imagery Esri, Maxar, Earthstar Geographics (2022). Research site imagery is displayed as RGB orthomosaic from UAV research flights.

## 3.4 Discussion

Our study provides empirical evidence of the effectiveness of simple threshold models for estimating leaf wetness compared to more complex machine learning models. Specifically, we found that leaf wetness models based on a relative humidity threshold (RH > 90%) and dew point depression (DPD < 2°C difference) performed equally well as the machine learning models. These findings align with previous proposals by Huber and Gillespie (1992) and Sentelhas et al. (2008) suggesting that empirical threshold models utilizing relative humidity and dew point depression can serve as reliable predictors of leaf wetness in field applications.

We applied both empirical and machine learning models to estimate leaf wetness across a coastal landscape during the summer fog season, which is characterized by excessive leaf surface wetting and warm temperatures that create a conducive environment for aboveground fungal diseases. Our analysis supports the hypothesis that a coastal-to-inland climate gradient influences the duration of leaf wetness.

Moreover, our investigation of canopy dieback in the manzanita species *A. tomentosa* revealed decreasing dieback farther from the coast. This trend was consistent between ground surveys and drone aerial imagery. In contrast, canopy dieback in *A. pumila* exhibited consistent patterns throughout its range. Dieback symptoms were more prevalent at coastal sites for *A. tomentosa* where it is less abundant and became less pronounced inland where it is dominant.

Preliminary greenhouse experiments supported this observation; inoculation caused greater *N. australe* disease severity in *A. pumila* than in *A. tomentosa* under drought stress soil water conditions (Detka, unpublished). These results suggest that *A. tomentosa* may exhibit greater tolerance to infection even under drought conditions, while *A. tomentosa* may be more susceptible to infection at the coast, where it experiences prolonged leaf wetting. The greater tolerance of *A. tomentosa* to dieback under drier, conditions may be a factor in the different natural distribution patterns of the two manzanitas, with *A. pumila* more common near the coast and *A. tomentosa* more common inland (Figure 3.8).

Differences in morphological traits and endemic ranges may explain the synergistic response of drought and disease in *A. pumila* and the tolerance of *A. tomentosa* to *N. australe* canker disease. *A. pumila* has a narrow endemic range, restricted to low-elevation coastal regions in the Monterey Bay region, while *A. tomentosa* is endemic to higher elevation, drier, windswept hillsides along the California coast. These drier, windswept regions are often engulfed in fog during summer, and light wind conditions during fog events may contribute to increased leaf wetting on *A. tomentosa*.

The observed differences in disease prevalence between the two manzanita species can also be attributed to their leaf hair morphological traits. The abaxial side of *A. tomentosa* leaves exhibited a denser coverage of matted woolly hairs (i.e. tomentose) compared to *A. pumila*. These trichome hairs can serve as a defense against herbivory (Levin, 1973), inhibit plant pathogen infection (Calo et al., 2006), and offer protection against plant stress factors such as UV radiation and water loss (Kaur & Kariyat, 2020). However, they may also contribute to prolonged leaf wetness, thereby increasing the likelihood of pathogen infection. Young woolly leaves of *A. tomentosa* emerge in late spring or early summer and are vertically oriented, providing protection against sun damage and water loss. Nevertheless, this characteristic may come at an ecological trade-off as young leaves could be more susceptible to fungal infection resulting from micro-scale leaf wetting and seasonal spore dispersal during periods of light winds and fog. Further research is necessary to understand the functional interaction between abaxial leaf trichomes and leaf wettability, as these structures may act to reduce leaf wetting as well (Brewer et al., 1991).

Notably, our observations of *N. australe* canopy dieback in *A. tomentosa* often coincided with extensive infestations of the microlepidoptera moth species *Tridentaforma fuscoleuca*. These moths lay their eggs in *A. tomentosa* leaves, resulting in the development of extensive leaf blister galls caused by the larvae (Detka et al., 2019). Leaf-mining insects, including flies (Variya & Bhut, 2014) and microlepidoptera (Afzal et al., 2023), are known to be associated with meteorological moisture conditions such as relative humidity and dew point. However, the direct association between fungal disease symptoms, *T. fuscoleuca* infestations, and leaf wetness remains unclear and requires further investigation to determine if *T. fuscoleuca* facilitates *N. australe* dispersal or infection.

The methodological choices for developing leaf wetness models were constrained by the availability of only one weather station collecting wind speed, wind direction, and solar radiation data. While machine learning models showed temporal correlations, the lack of replicate stations limited our ability to capture variation in these factors across a coastal-to-inland gradient. Moreover, additional stations at the coast are necessary to determine the role of microclimate conditions dependent on topography. The most coastal station in our study was also located in a terrain depression, which may explain the higher relative humidity values and lower mean air temperatures observed at that location. All nearby meteorological stations deployed on ridgelines were vandalized and destroyed, resulting in insufficient data to investigate the role of topography.

For future research, we recommend further investigation into the utility of empirical threshold models and machine learning models for leaf wetness estimation in different California coastal environments including higher altitudes and across latitudinal gradients. California is home to 62 species of manzanitas, with 49 being endemic to the Pacific coastal region and may make it an excellent model genera to study the influence of micrometeorological conditions on plant disease. Additionally, incorporating reliable leaf wetness sensors into low-cost weather station units would enable greater replication across a larger coastal to inland gradient. Standardized commercial sensors may not accurately represent the variation in leaf traits among species that directly influence leaf wetness duration (e.g., waxy adaxial cuticle, tomentose abaxial). Exploring the integration of more lightweight and inexpensive sensors, such as the one developed by Nguyen and others (2023) that mimic leaf characteristics could be beneficial.

The results of our study imply that the wet conditions of coastal sites may negatively impact the canopy health of *A. tomentosa* through increasing disease-related dieback, restricting its distribution to more inland sites while allowing *A. pumila* to thrive in more coastal areas. Future research avenues need to address the confounding influence of herbivory from mammals and insects through herbivory exclusion experiments with inoculations in the field, together with greenhouse experiments.

In conclusion, our study of the association between leaf wetness and aboveground fungal diseases in California coastal shrublands, and the effectiveness of simple estimates of leaf wetness duration from readily available air temperature, relative humidity, and dew point depression. By comprehending the dynamics of plant pathogens in these ecosystems during non-disturbance periods, we can enhance management and conservation strategies, particularly considering the varying susceptibility of closely related species to plant pathogens.

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# Chapter 4

# U.S. Civil Drone Regulations: Promoting Safety, Protecting Privacy, and Fostering Beneficial Uses

> If the mind of man can invent and operate a flying machine, it ought to be able to devise a rule of law which is adequate to deal with the problems flowing from such an inventiveness.
>
> - Supreme Court of Oregon (1960). Atkinson v. Bernard, Inc., 223 Or. 624, 355 P.2d

## 4.1 Introduction

Few surveillance technologies have entered widespread use in society without raising significant concerns about safety, security, and privacy. (Lyon, 2001; Widmer & Albrechtslund, 2021). Remotely piloted drone aircraft are an increasingly routine part of civilian life, used regularly by land managers, emergency responders, contractors, businesses, artists, and hobbyists. This rise in familiarity and usefulness is paralleled by increased concerns about the potential threats that untrained or irresponsible drone pilots pose for safety and privacy (Stoica, 2018). Historically, the tensions over legal and policy jurisdiction have prevented the integration of ethical frameworks and best practices to protect privacy from being incorporated into training and assessment for drone pilot certifications. Such gaps create social conflicts and legal uncertainties in current use of drones.

Drones are widely used in a variety of applications including playing an important role in wildfire management, allowing land managers and first responders to efficiently and safely monitor large remote regions (Mbaye et al., 2023). However, the careless operation of drones by curious public recreationalists, seeking to catch a glimpse of active wildfire, creates safety hazards for firefighting aircraft and ground crews and disrupts fire suppression operations. During U.S. disaster responses, the Federal Aviation Administration often implements a Temporary Flight Restriction order that bans use of recreational drones in the active wildfire region to protect aircraft involved in wildfire operations (14 C.F.R. § 91.137, 1989). Despite these restrictions, between 2016-2020, the U.S. Forest Service reported 93 incidents of civilian drone incursions within active wildfire areas in the western states. Two-thirds of those incursions interrupted aviation wildfire suppression operations above federal land and the remaining incidents directly jeopardized the safety of crewed aircraft and ground support (Kolarich, 2017). Public utilities, safety agencies, and insurance companies use drones to survey property damage and situational risks as part of the disaster relief process after wildfires (Daud et al., 2022). But this same disaster recovery technology has the potential to be used by unscrupulous looters casing evacuated properties for opportunities to trespass, rob, or burglarize (Nelson & Gorichanaz, 2019; Adnan & Khamis, 2022).

Drone surveillance systems offer support for law enforcement officers tasked with maintaining public order and rendering public assistance by documenting accident and crime scenes, apprehending suspects, monitoring public safety during events, and providing first responder care. Law enforcement agencies have applied surveillance systems to investigate crimes and track potential criminal activity using stored imagery and geographic information systems to associate people with places and events, raising a host of ethical issues related to: privacy, trust, autonomy, cause, and authority (Feeney, 2020). While the potential for these systems to increase public safety and add security is welcomed, they also come with a large cost to privacy from pervasive location tracking and stockpiling of sensitive personal information. The pervasiveness of drone overflight can also have a chilling effect that inhibits participation in constitutionally protected activities such as political rallies, protests, and religious ceremonies. This is especially true in communities of color, where there is over-policing in terms of surveillance and under-policed when it comes to emergency services (Heh & Wainwright, 2022; Gordon, 2022).

Advances in computer vision and drone autonomous flight has also raised privacy concerns. Drones use autonomous obstacle avoidance technology, computer vision, and artificial intelligence algorithms to prevent drones from colliding with objects in their flight path. While this technology enhances drone safety, it raises privacy concerns. For example, a drone that uses obstacle avoidance technology to avoid colliding with structures when operating in a populated area may inadvertently collect sensitive data about individuals and their location, behaviors, and associations. This raises concerns about invasion of privacy, especially if the drone is being used for commercial purposes or surveillance by law enforcement agencies. Drone manufacturers are developing obstacle-avoidance technologies designed to respect privacy by not collecting detailed images or data about the surrounding environment, or by automatically blurring images collected in sensitive areas to avoid using information beyond its originally intended purpose. Despite these privacy protection advances, the use of drone obstacle avoidance technology can still raise privacy concerns, and it is critical that drone operators remain transparent about the purpose of flight operations and respect the privacy rights of individuals and property owners.

Technological advances in drones are fueling expansion of their domestic application. Although many applications can contribute to social good, the rapidly expanding civilian use and their sensing capabilities raise complex technical and policy issues related to safety and privacy that have not yet been resolved (Wicker et al., 2020). Drones can benefit society as tools for enhancing public access to goods and services (Scott & Scott, 2019; Guillen-Perez et al., 2016; Haider et al., 2022), assessing safety (Roldán-Gómez et al., 2021; Van Tilburg, 2017), increasing efficiency (Rejeb et al., 2022; Park et al., 2020), supporting environmentally friendly practices (Chiang et al., 2019), and providing recreational enjoyment (Hildebrand, 2021). But the growing application of drones comes with increased aerial traffic and heightened concern for safety risks caused by reckless or negligent pilot behavior that may cause collisions with manned aircraft, other objects, and bystanders. Additionally, the rapidly expanding use for surveillance by private actors, organizations, and governments have raised concern about the impacts on privacy, civil rights, and civil liberties (Obama, 2015; Sabino et al., 2022; Scharf, 2018; Brobst, 2019). Inexpensive drones with compact designs and advanced information-gathering capability have heightened the potential for individuals, organizations, and governments to acquire, store, and use pervasive information about individuals or groups (West & Bowman, 2016; S.631 - 115th Congress, 2017; *ACLU V United States Customs and Border Protection, et al.*, 2021). In addition, nefarious actors can use drones, and the data gathered from them, to breach public safety measures at sensitive sites and act with criminal intent (Swales, 2019).

Here I explore historical, legal, policy, and training aspects of drone use that inform how to achieve civil aviation safety and privacy protection while not impeding beneficial uses of uncrewed aircraft. I first summarize the legislative history of civilian drone integration in the U.S. national airspace. Next, I explore the current regulatory frameworks with a focus on federal safety requirements for commercial pilots and the evolving landscape of state statutes that address drone aerial trespass and privacy rights issues. I highlight key court cases that have shaped current legal precedent and subsequent protections for unreasonable drone aerial invasions of privacy in the U.S. national airspace. Lastly, I explore the potential strengths and challenges of a federal-state drone regulatory status quo.

## 4.2 A Brief Legislative History of Drones in U.S. Airspace

Drones are uncrewed aircraft systems (UAS) that include an uncrewed aerial aerial vehicle that can be controlled remotely by a human pilot or can operate autonomously using advanced onboard processors and sensors, control software, and global positioning systems (GPS). Drones are distinquished from other model aircraft, which are entirely human-operated by remote control and are not equipped with the advanced sensors, software, and autonomous capabilities found in UAS. Most domestic drones used in the national airspace fit the definition of, "small unmanned aircraft system (sUAS) weighing less than 55 pounds on takeoff, including everything that is on board or otherwise attached to the aircraft" (14 C.F.R. § 107, 2016). sUAS regulations cover all the associated components (i.e., communication links, navigation systems, sensors, controllers) required for the safe and efficient operation of the aircraft in the national airspace system (49 U.S.C. § 44801, 2018; 14 C.F.R. § 107.3, 2016).

We use the colloquial term 'drone' or gender-neutral technical terms "uncrewed aerial vehicle" and "uncrewed aircraft system" throughout to describe remotely piloted "unmanned" aircraft permitted by the Federal Aviation Administration (FAA) to operate in U.S. national airspace. We acknowledge that the term 'drone' is not gender-neutral, with references to males in insect colonies (e.g., ants, bees) and its origin in highly male-gendered remote-pilot warfare (Clark, 2019; Joyce et al., 2021). Gendered terminology is a systemic problem in aviation, and we adopt these terms as academics to support the continued development of a diverse and inclusive aviation culture.

In the U.S., drones meeting the sUAS definition need to be registered with the FAA, with the exception of those that weigh 0.55 pounds or less (less than 250 grams) that are flown exclusively for enjoyment and not for work, business, compensation, or hire (84 FR § 22552, 2019). Drones used for commercial operations need to be registered regardless of their weight (14 C.F.R. § 107, 2016). There are an estimated 872,248 federally registered drones currently operating in the U.S. with 39% registered as commercial drones and 61% registered as recreational aircraft (FAA, 2023). Fewer than 0.1% (3,880) registered aircraft are classified as experimental aircraft for research purposes and have exemptions (49 U.S.C. § 44807, 2018). These values likely underestimate the true number of drones operating in the U.S. since many recreationalists operate aircraft that are below the 250g requirement for registration. The FAA estimated that by the end of the fiscal year 2023 there would be approximately 1.75 million drones registered to recreational pilots and 801,000 drones registered as commercial aircraft (FAA, 2022). To place the estimated number of registered drones in perspective, consider that the 2021 U.S. Department of Transportation estimated there were about 210,000 U.S. registered conventional (i.e., crewed) aircraft currently in operation in national airspace; that the number has remained relatively stable since 2016 (median = 218.7, IQR = 6.61) (U.S. Bureau of Transportation Statistics, 2023).

In the U.S., UAS remote pilots are federally certified by the Federal Aviation Administration through two assessment pathways that depend on the nature of flight operations. As of 2016, commercial UAS pilots operate under the FAA's rules in Title 14 of the Code of Federal Regulations (14 CFR) part 107, section 107.73(a), codified in 14 C.F.R. § 107 (also termed the "Section 107" or "Part 107") and as part of these rules must obtain a Remote Pilot Certificate with a "Small Unmanned Aircraft Systems Rating" from the FAA by passing a written Aeronautical Knowledge test. In other words, to become a commercial drone pilot, one needs to pass the required written examination administered by a recognized Airman Certificate Testing Service (ACTS) (`https://faa.psiexams.com`). The assessment is focused on safety and evaluates knowledge of FAA sUAS flight rules and registration regulations, requirements for operation over people and moving vehicles, night operation, effects of drugs and alcohol, general national airspace system regulations, interpreting aeronautical sectional charts, airport communications and operational protocols, impacts of weather and micrometeorology, flight operation limits, and aeronautical decision making. Notably, certification requires no additional assessment of UAS operational flight proficiency or knowledge of best practices for protecting privacy, maintaining transparency, and ensuring accountability.

The "Remote Pilot sUAS Study Guide" materials currently approved by the FAA for the Part 107 exam (FAA-G-8082-22, 2016) contain no guidance regarding compliance with state and local laws pertaining to trespass, privacy, or negligence. Existing Part 107 certified remote pilots are required to complete a recurrent training every 24 calendar months; the current recertification training contains a notice related to privacy issues stating that "state and local privacy laws may apply to sUAS operations." The training module also reminds remote pilots that they are "responsible for reviewing and complying with such laws prior to operation." Remote pilots are further encouraged to review the "Voluntary Best Practices for UAS Privacy, Transparency, and Accountability" developed as part of a multi-stakeholder meeting convened by the National Telecommunications and Information Administration (NTIA) but the FAA provides no training in the application of these practices (NTIA, 2016).

Recreational drone operators must pass a less extensive examination that assesses minimal aeronautical knowledge, federal regulations, and recommended safety best practices through "The Recreational UAS Safety Test (TRUST)" exam (49 U.S.C. § 44809, 2018). The TRUST certification process is free of charge and has no expiration date. The TRUST exam and preparatory materials provide no guidance about state or local privacy laws. All recreational drone operators must provide proof of TRUST certification if requested by law enforcement or FAA personnel. As of 2023, there were an estimated 757,131 active remote pilots, including 41% commercial operators (Part 107 certified) and 59% with recreational certificates (TRUST) (FAA, 2023). Model aircraft operators must satisfy all the exemption criteria specified in 49 USC §44809 or they must meet Part 107 compliance.

The final class of remote pilots are public operators. Public operators are Part 107 certified pilots associated with public agencies that conduct flight missions for governmental purposes. Public operator organizations must obtain a Certificate of Waiver or Authorization (COA) from the FAA that specifies how the drone will be used. The purpose of the FAA COA is to allow certain UAS operations that FAA regulations would otherwise prohibit. The COA grants specific permission and limitations for UAS operation in specific types of locations for a defined period. COAs are typically issued for operations that will be conducted for public benefit or interests of national security including: research and development, law enforcement, or emergency response. The FAA evaluates each COA application on a case-by-case basis, and may require additional safety measures or modifications to the operation before granting the COA.

The number of commercial (Part 107 certified) remote pilots has continued to increase annually since 2016 when the FAA started issuing remote pilot certificates (Figure 4.1). In contrast, the number of active U.S. conventional (crewed) aircraft pilots has remained relatively constant (Figure 4.1). The growth in the number of certified remote pilots is mainly associated with a rapidly expanding UAS market expected to be worth $92 billion by 2030 (Allied Market Research, 2020) and the need for skilled UAS professionals to fill an estimated 100,000 new U.S. jobs by 2025 (D. Jenkins & Vasigh, 2013). Part 107 remote pilot certifications represent a variety of UAS sectors and commercial activities with the most growth within government agencies, telecommunications, drone service operations, infrastructure, and assembly integration.

The federalist system of the U.S. government assigns specific powers to the federal government and others to state governments, with restrictions on federal preemption. The current political period in this system is one of increased federal laws, regulations, and rules that have imposed demands on states without providing the funding necessary to meet compliance. This escalates state-side concerns about federal regulations and legal disputes related to the role of the federal system, with court rulings tending to favor the states (Boyd & Fauntroy, 2020). Current policy challenges associated with drone regulation stem largely from states' concern about federal regulations that focus on public safety without consideration for property rights and personal privacy. Such policy challenges are especially complicated because drones operate at an altitude that places them in a divided jurisdiction between federal regulation of airspace safety and states' regulatory responsibilities to protect people's property rights and privacy. This tension requires

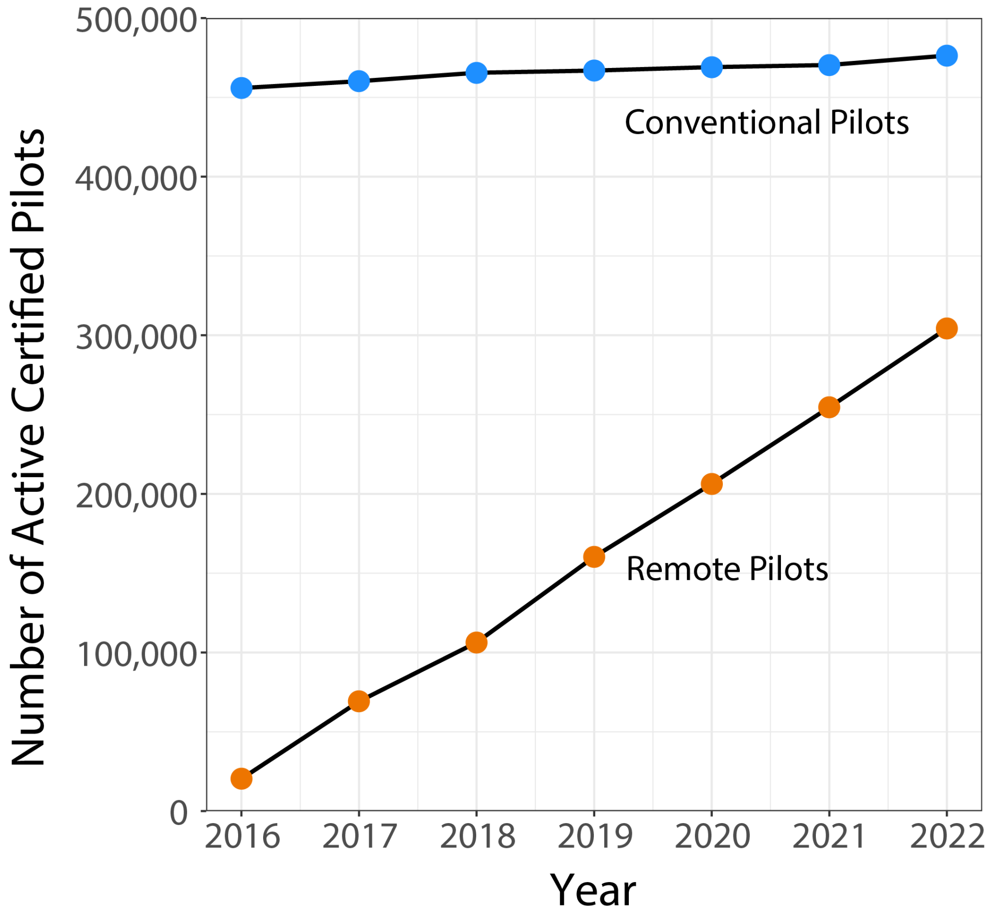


Figure 4.1: Estimated number of active U.S. certified conventional aircraft pilots and certified (Part 107) commercial remote sUAS pilots 2016-2022. Number of active U.S. certified conventional aircraft pilots does not include the student pilot category. Data source: U.S. Federal Aviation Administration Civil Airmen Statistics annual reports (2016 - 2022). Reported estimates based on official airmen certification records maintained at FAA's Aeronautical Center, Oklahoma City, Oklahoma. Reports available at: https://www.faa.gov/data$_research.Accessed: April20, 2023.$

a look at the historical and legal basis for this conflicted airspace jurisdiction, and consider drone impacts on the usefulness of private property as well as reasonable expectations of privacy.

Trespass (Torts § 158) is the unlawful intrusion of an individual into someone else's property without their permission, irrespective of harm caused (American Law Institute, 1965). Drones pose a challenge for trespass analysis since the drone itself encroaches into the airspace above the land but never physically touches land property. The common law principle of property rights emerges from the thirteenth-century Latin maxim; *"cuius est solum eius est usque ad coelum et usque ad infernos"* (Latin for "whoever owns the soil it is theirs up to the heavens and down to hell", usually abbreviated as the *ad coelum* doctrine) (Fellmeth & Horwitz, 2011). This might suggest that the drone has trespassed once it has entered the airspace above the property. However, in the age of modern aeronautics what constitutes an aerial trespass is more complex. The current U.S. concept of aerial trespass is based largely on a seminal Supreme Court case *United States v. Causby* (1946), which upheld the Taking Clause of the Fifth Amendment to the U.S. Constitution associated with the use of airspace above private land (U.S. Const. amend. V). In *Causby*, Thomas Lee Causby owned a chicken farm near an airport used regularly by the United States military for low-altitude bomber flight training operations during WWII. Causby claimed that noise from low-flying aircraft exercises resulted in the extensive deaths of his chickens and forced him to abandon his poultry business. Causby filed suit under the *ad coelum* doctrine arguing that he owned the airspace above his farm and that the military activities were a form of confiscation of property without compensation under the Taking Clause of the Fifth Amendment of the U.S. Constitution. The Court accepted Causby's claim on the grounds of a Fifth Amendment violation and ordered the government to compensate him. However, the Court, in judicial dictum, rejected the *ad coelum* doctrine stating that it, "has no place in the modern world" (*United States v. Causby*, 1946). It further noted that if the Court were to accept the doctrine as valid, "every transcontinental flight would subject the operator to countless trespass suits. Common sense revolts at the idea" (*United States v. Causby*, 1946). The Court further acknowledged that a property owner has rights of ownership extended to the "superadjacent airspace" defined as, "at least as much of the space above the ground as they can occupy or use in connection with the land." (*United States v. Causby*, 1946). This superadjacent airspace principle considers aircraft overflight to be lawful unless the altitude is so low that the flight path interferes with the existing use of land or poses an imminent danger to persons or property on the land. In the Restatement (Second) Tort (§ 159) "flight by aircraft in the air space above the land of another is a trespass if, but only if: (a) it enters into the immediate reaches of the air space next to the land, and (b) it interferes substantially with the other's use and enjoyment of his land". Drone traffic in the superadjacent airspace could be a disruption of the quiet use and enjoyment of solitude that private property provides. A property owner could pursue a cause of action for private nuisance (§ 159) based on annoyance from drone noise (i.e., propeller noise). To the best of our knowledge no litigation in response to drone-related noise has occurred yet. Future lawsuits may emerge with increased drone traffic but technological advances and higher flight altitudes have been shown to greatly reduce drone noise and noise annoyance levels (Torija & Nicholls, 2022).

The legal definition of a "superadjacent airspace" provided the persuasive authority for additional litigation and led to the development of the Federal Aviation Regulations (FARs) which are rules prescribed by the Federal Aviation Administration (FAA) governing all aviation activities in the United States. The FARs currently make up Title 14 of the Code of Federal Regulations (CFR) and include aviation safety rules related to design, maintenance, flight operations, training activities, lighter-than-air aircraft, kites, structural heights, lighting obstructions and markings, model rocket and model aircraft operations, and commercial space operations. Title 14 CFR rules set the floor for navigable airspace by crewed aircraft at 500 feet above the surface unless the aircraft is maneuvering for takeoff or landing (14 C.F.R. § 91.119, 1989). There are some aircraft exceptions to this regulation (e.g., kites, hang gliders, helicopters, and flight in unpopulated areas) and they have additional restrictions that limit their physical distance to people, objects, and structures (14 C.F.R. § 91.119, 1989). The Restatement (Second) of Torts (§§ 158, 159(1)) addresses issues of aerial trespass whereas the intention of the federal regulation is focused on partitioning airspace for safety and reducing the potential for collisions between crewed and uncrewed aircraft.

In 2016, the Federal Aviation Administration (FAA) released the final rule for Small Unmanned Aircraft Systems (sUAS) Regulations setting the maximum allowable altitude for drone operations at 400 feet above the ground, or higher if the drone remains within 400 feet of a structure and does not enter controlled airspace (14 C.F.R. § 107, 2016). This regulation was intentionally designed to provide a safety buffer (100 feet) between uncrewed drone operations and crewed aircraft operations, which start at 500 feet. Prior to the Part 107 final rule, the space below 500 feet could be considered within the jurisdiction of the state, and protected by the 10th Amendment to the U.S. Constitution, and in accordance with federal minimum safe altitudes for crewed aircraft (14 C.F.R. § 91.119, 1989). But since 2016 and the implementation of the Part 107 rule, Federal standards legally restrict drones to travel only in the superadjacent airspace; in the strict definition of civil tort law this means that drones, which are classified as aircraft by the FAA, are committing aerial trespass when operating outside of navigable airspace. This created significant challenge to existing tort law, and states responded by pursuing the Drone Federalism Act of 2017 (S. 1272) (S.1272 - 115th Congress, 2017). This act proposed reducing the FAA's preemption for drone regulations and giving states regulatory authority over drones in the "immediate reaches of the airspace above property" as a means for preserving property rights, protecting privacy, ensuring public safety, and restricting nuisances and noise pollution.

Central to the bill was a proposed bright-line restriction of civil (i.e., non-military) UAS as excluding "(1) any area within 200 feet above the ground level of the property or any structure on the property; and (2) any area where operation of the aircraft system could interfere with the enjoyment or use of the property." The motivation for this bill came from a ruling by a federal court of appeals finding that the FAA lacked the authority to regulate drone use by hobbyists (H.R.658 - 112th Congress, 2012), raising concern that the lack of regulation would fail to rectify issues of privacy and trespass by drone recreationalists. The bipartisan bill (S. 1272) was introduced but it did not become law out of concern that the minimum altitude limits would impede commercial uses of drones that operate at lower altitudes for legitimate business reasons (e.g., structural inspections, drone delivery, search and rescue). In response to state concerns, the National Conference of Commissioners on Uniform State Laws drafted the Uniform Tort Law Relating to Drones Act (NCCUSL, 2019) that did not include a minimum operating altitude. Established in 1891, The Uniform Law Commission (ULC), also known as the National Conference of Commissioners on Uniform State Laws (NCCUSL) is a non-profit group comprised of appointed state commissioners from each state that provide states with non-partisan legislation in order to establish stability and uniformity in areas of state statutory law. The Draft Model Act (2019) outlined ten criteria for consideration in analysis of drone aerial trespass:

1. The amount of time the unmanned aircraft was operated over the landowner's property;
2. The altitude at which the unmanned aircraft was operating;
3. The number of times unmanned aircraft have been operated over the property;
4. Whether the unmanned aircraft recorded or captured audio, video or photographs while in operation over the property;
5. Whether the landowner has regularly allowed operation of unmanned aircraft over the property;
6. Whether the operation of the unmanned aircraft caused physical damage to persons or property;
7. Whether the operation of the unmanned aircraft caused economic damage;
8. The time of day the unmanned aircraft was operated over the landowner's property;
9. Whether an individual on the land saw or heard the unmanned aircraft while it was over the property; and,
10. The operator's purpose in operating the unmanned aircraft over the property.

The Draft Model Act criteria are aimed largely at evaluating if the aircraft interfered with the use of the land (i.e., criteria 1-3, 5-7,9), rather than if an intrusion of airspace and invasion of privacy has occurred (i.e., criteria 4, 8, 10). This is problematic under the Restatement (Second) Tort (§329) for trespass because a landowner has the right to claim trespass for intrusion – regardless of if harm has been committed. States have not accepted the Draft Model Act approach to defining aerial trespass since the responsibility of protecting property owner trespass rights would require determining if trespass (§329) and nuisance (Tort Restatement §822, §826-829, §831) has been committed based on an evaluation of the degree of interference that the drone flight activity has had on the usefulness of the land. Instead, states have adopted trespass doctrines to drone aerial intrusion utilizing existing civil trespass law (e.g. Tort § 158). States have successfully defined trespass as entering private land or airspace without permission, and specifying consideration of compensable trespass injury in circumstances that violate a reasonable expectation of privacy (§ 652). I explore the efforts of states to enact privacy invasion regulations in the next section.

### 4.2.1 Regulation of Privacy Invasion by Drones

Many current efforts to protect property rights from drones (i.e., trespass) are actually motivated by concerns about risks to privacy. Privacy tort law and constitutional law often serve as critical lenses for assessing the design and use of emerging surveillance and security technologies. The general law of privacy from civil tort law addresses unlawful invasion of privacy by private (civil) actors, and the constitutional right of privacy protects personal privacy against unlawful governmental invasion.

In this work, I define privacy as an individual or group's ability to maintain a state of seclusion and selectively choose what information and forms of self-expression are shared with others. This definition is inspired by concepts presented by Judith W. DeCew (1997), "In pursuit of privacy: Law, ethics, and the rise of technology" and Daniel J. Solove (2002), "Conceptualizing Privacy". A seminal definition of privacy comes from Aristotle's - Book One of Politics where he describes the value of separate spheres of public (political, *polis*) and domestic life (home culture, *oikos*) that allow an individual to delineate a protective boundary between personal life and public scrutiny (Swanson, 1994). In the U.S., two historic definitions of privacy used today are “the right to be let alone” and “an individual’s right to seclusion, or right to be free from public interference”. These definitions of privacy were originally defined in the December 15, 1890 issue of the Harvard Law Review in an article entitled "The Right to Privacy," written by attorney Samuel D. Warren II and then future U.S. Supreme Court Justice Louis Brandeis in response to the invention and increased accessibility of celluloid photographic film (R. Jenkins, 1975). Warren and Brandeis raised concern that the ability to capture “instantaneous photographs” and widely distribute images via the “newspaper enterprise” have “invaded the sacred precincts of private and domestic life” (p.195) (Warren & Brandeis, 1890). The simplicity of the Warren and Brandeis privacy definition has appeal but scholars posit that privacy is more complex than the right to be free of public interference or maintain seclusion (Westin, 1968; DeCew, 1997). In “Privacy and Freedom” (1968), Alan Westin further defined privacy in terms of informational privacy, largely in response to increased concern and conflict between privacy and emerging surveillance technology (i.e., closed-circuit television and video camera surveillance), and increased information storage capabilities (i.e., computer memory). Westin provides a definition for informational privacy as “the ability to determine for ourselves when, how, and to what extent information about us is communicated to others” (p. 5). Most recently Finn et al. (2013) described seven distinct types of privacy based on the predominantly Western view of a right to privacy. The Western concept of a right to privacy is based on the 18th-century Enlightenment view of the individual as the focus of society with each individual possessing the right to live and act without interference from others so long as society is protected from what is deemed unreasonable acts. According to Finn et al. (2013, p. 7-10) these privacy rights include:

- the person (e.g., bodily, medical, reproduction, self-determination)
- behavior and action (e.g., movement, habits)
- communication (e.g., spoken word, phone, mail, email)
- data and image

- thoughts and feelings
- location and space (e.g., home, rooms, safe/lockbox)
- association (e.g., friends, family, group membership/affiliation).

The U.S. Constitution, U.S. Bill of Rights, and civil tort laws offer some privacy protections. Although the U.S. Constitution contains no express right to privacy, the U.S. Bill of Rights does protect specific aspects of privacy from government surveillance including the privacy of beliefs (1st Amendment) and privacy of the person and possessions against unreasonable searches (4th Amendment). Privacy tort laws also provide individuals with an actionable right to be free from the invasion of privacy and have provided the foundation for local and state governments to enact ordinances and laws placing restrictions on drones in order to protect citizens from an invasion of privacy (§ 652 B-D). Violations of privacy include:

1. § 652B Intrusion Upon Seclusion: "One who intentionally intrudes, physically or otherwise, upon the solitude or seclusion of another or his private affairs or concerns, is subject to liability to the other for invasion of his privacy, if the intrusion would be highly offensive to a reasonable person."

2. § 652C Appropriation of Name or Likeness: "One who appropriates to his own use or benefit the name or likeness of another is subject to liability to the other for invasion of his privacy."

3. § 652D Publicity Given to Private Life: "One who gives publicity to a matter concerning the private life of another is subject to liability to the other for invasion of his privacy, if the matter publicized is of a kind that
(a) would be highly offensive to a reasonable person, and
(b) is not of legitimate concern to the public."

The laws regarding aspects of drone use and privacy are still in the early stages of development as the FAA and other federal agencies (i.e., DOT, DHS) develop key aspects of its UAS safety and security requirements and as the number of state civil court decisions related to drones and privacy tort occur. As early as

2013, approximately 45 U.S. states considered enacting restrictions on drones and formally expressed concern about the potential impacts of UAS on public safety and privacy (National Conference of State Legislatures, 2023). In response to this concern, the FAA released a fact sheet outlining examples of UAS laws that would likely fall within state and local government authority, such as requirements for police warrants before using UAS for surveillance; amending state statutes on voyeurism to include the use of UAS; exclusions on using UAS for hunting or fishing, or harassing individuals engaged in those activities; and restrictions on weaponizing a UAS (FAA, 2015).

This FAA response was prompted partly by growing state-level concerns and an increasing number of crewed aircraft pilot-reported incidents involving unauthorized and unsafe use of UAS (238 aircraft pilot sightings were reported in 2014, increasing to 780 in 2015 with several in regions of wildfires across the western U.S.) (FAA, 2015). This response was also aimed at clearly delineating what is and is not in the expressed authority of the FAA as a federal agency. In the fact sheet, the FAA reiterated its commitment to the congressionally vested scope of safety and security of national airspace and its continued enforcement of safety-related requirements for the operation of UAS in U.S. airspace. The FAA cautioned that "substantial air safety issues are raised when state or local governments attempt to regulate the operation or flight of aircraft" (p. 2). This action also served as a reminder to state legislatures and local governments that they cannot enact laws and ordinances that preempt federal laws (U.S. Const. art. IV, § 2.), and in turn, federal agencies cannot intervene in matters of the state (e.g., policing, civil invasion of privacy, land use zoning). The FAA closes by outlining specific examples of operational UAS restrictions that would require consultation with the FAA. The FAA is able to place temporary and permanent airspace restrictions over cities and specific distances from national landmarks but these restrictions are heavily scrutinized by the FAA for their effect on national security, public safety, and airspace efficiency. Issues of trespass and privacy concerns are not considered in these airspace restriction requests.

### 4.2.2 The Current Drone Legal Privacy Landscape

Since 2015, civil litigations and criminal prosecutions continue to emerge in federal and state courts as citizens object to drone operations that are viewed as aerial trespass and violating a reasonable expectation of privacy. Since 2013, 39 of the 50 U.S. states have passed legislation that directly addresses privacy rights and drone use for all areas outlined in the FAA's factsheet (FAA, 2015; National Conference of State Legislatures, 2023). The following court cases have provided precedent for the developing U.S. civil drone legal landscape governing privacy concerns.

The earliest court case addressing drone invasion of privacy followed shortly after the authorization for integration of civil unmanned aircraft systems into the national airspace system (H.R.658 - 112th Congress, 2012). *Beesmer v. Ulster, N.Y.*, was the first court case that specifically addressed drone invasion of privacy. David Beesmer, a professional videographer, was flying his drone outside a medical facility in Lake Katrine, N.Y. while waiting for his mother during her appointment at the Mid-Hudson Medical Group building. Beesmer was arrested by Ulster City police and charged with misdemeanor attempted unlawful surveillance. Prosecutors stated that the drone was near the fourth floor, which had exam rooms occupied by hundreds of patients that had a reasonable expectation of privacy. The defense (Beesmer) successfully argued that a reasonable expectation of privacy was maintained as: (1) windows were tinted and (2) he checked with employees about flying his drone to capture footage, and (3) shared footage with employees for review with the intention of securing the medical group as a client for his business. Beesmer was acquitted of all misdemeanor unlawful surveillance and invasion of privacy charges on the grounds of "no legitimate purpose", meaning that he was in no way acting in a malicious or threatening fashion, and made his intentions clear to facility management that he was seeking to secure the organization as a possible client for his growing drone-based videography freelance business – prior to conducting his flight operations. This lawsuit set precedent for other states to design their drone regulatory laws with clearly defining intent as grounds and the need for legitimate attempts at communication with those parties whose reasonable expectation of privacy may be jeopardized.

In *Boggs v. Merideth* (January, 2016), John D. Boggs pursued federal criminal charges against William H. Merideth after he shot down Boggs' drone. Boggs (plaintiff) sought a declaratory judgment for damages to his drone on the grounds that his actions did not infringe on Merideth's reasonable expectation of privacy, and that property owners cannot shoot at aircraft (crewed or uncrewed) flying in approved federal airspace. Ultimately the case was dismissed based on a "lack of subject matter jurisdiction", meaning that the case was deemed inappropriate for federal court, and was a matter for the state court to decide given the need for a legal decision regarding civil privacy rights and property rights. It is unclear if the courts would have found that Merideth's privacy was invaded or property trespassed because while Kentucky law defines curtilage trespass as "an intended or negligent encroachment onto another's property that is not privileged", the state also has an Adverse Possession law (Ky. Rev. Stat. § 411.120, 1942) which allows people who trespass or encroach on the private property of another a minimum period of time to develop an ownership claim to the property. A successful adverse possession claim in Kentucky must satisfy five elements: the trespasser's possession must be (1) actual, (2) hostile, (3) exclusive, (4) open and notorious, and (5) continuous. Boggs provided the drone's recorded flight log GPS locations as evidence to the contrary for trespass and invasion of privacy by showing that the flight path was not over, or encroaching on Merideth's property. However, it remains unclear if in states like Kentucky that continue to have Adverse Possession law (Ky. Rev. Stat. § 411.120, 1942) whether Boggs' actions could be viewed as an open and notorious attempt to survey property for future possession claims. Boggs' pursued the case in federal court as a likely attempt to have the court create a clear rule for drone operation in approved superadjacent airspace, but without the FAA's direct involvement in the case it was unsuccessful. Meridith was cleared of first-degree endangerment and criminal mischief, setting a potentially dangerous precedent that risked inadvertently justifying the willful destruction of personal property (i.e., chattel trespass) when a property owner deems that the user's actions are violating either property rights (trespass) or privacy rights. In April 2016, the FAA responded publicly confirming that shooting down any aircraft is a federal crime under the 18 U.S.C. § 32; that makes it a felony to damage or destroy an aircraft regardless of the situation because the act poses significant safety hazards (Goglia, 2016). This case also demonstrated the level to which the federal courts and the FAA could get involved in state matters where a landowner's privacy and a UAS property rights are at odds. A landowner has a legal right to privacy and to enjoy their property free from nuisance or trespass and owners of personal property have the right to not have their property damaged or taken. The intentional downing of a drone over private land sets these two rights against one another and brought additional attention to states for the need to contextualize privacy invasion concerns in future law. Notably, if had Boggs brought federal charges against Merideth specifically for the willful damage or destruction of an aircraft the case may have had a very different outcome in a federal court (18 U.S.C. § 32, 1984).

Only one federal court has ruled on the merits of preemption for a city's local ordinance banning drones within city limits (*Singer v. City of Newton*, 2017), but this case has set clear precedent for the design of state laws and local ordinances. In January 2017, physician-inventor Dr. Michael Singer filed a lawsuit in the federal district court of Massachusetts against the City of Newton after they banned his drone-based emergency medical services system. The City of Newton enacted an ordinance that required landowner's consent to fly a 'pilotless aircraft' in an attempt to protect privacy (i.e., voyeurism) but the law as designed was in Singer's view preemptive to federal regulations. The law required: (1) that all owners register their pilotless aircraft with the city clerk's office; (2) banned flight below 400' over private property without the landowner's consent or over any city or school property without the city's permission; and (3) aircraft in flight needed to remain within the operator's line of sight. Singer successfully argued that the ordinance was conflict preemptive in three instances. First, Singer could not comply with both the city ordinance limiting drone traffic to fly above 400' and the federal rule limiting drone traffic to fly no higher than 400' above the ground or above a structure. Second, the city provision prevented drones from flying over public property with no expressed altitude ceiling, meaning that the regulation would conflict with federal airspace regulations by restricting all types of air traffic over designated public spaces. Lastly, the provision requiring drone registration with the City of Newton was conflict preemptive on the grounds that the FAA already requires drone pilots to comply with federal registration standards for drone aircraft and the state cannot restrict flight based on a citywide aircraft registration statute. The courts recommended that the city redraft the ordinance to avoid conflict preemption and implement it in the future. The court also suggested using the terms 'uncrewed' or 'remotely piloted' over 'pilotless' in order to hold the remote pilot in command (PIC) as the responsible party and address the fact that UAS are not actually 'pilotless'. The City of Newton complied with the recommendations and revised the ordinance by defining 'pilotless aircraft' as "unmanned aircraft systems, or drones", and set prohibitions that "no UAS shall be operated: 1) over any property in a manner that causes direct and immediate interference with the use or enjoyment of that property". The revised ordinance also addresses unwarranted surveillance, voyeurism, harassment, assault, public nuisance, and trespass (Newton 20 § 20-64, 2022). There are still existing municipal laws that attempt to enforce citywide bans on drone traffic (e.g., St. Bonifacius, Minnesota —Municipal Law // 2013 § 91) but it is likely that precedent from preemptive lawsuits (e.g., *Singer v. City of Newton*) will lend to their failure in future litigations.

Court cases have also challenged the use of drones by government entities, where persons have a reasonable expectation of privacy in their property and protections from unwarranted search and seizure under U.S. Constitutional Fourth Amendment rights. In the Michigan court, *Long Lake Township v. Maxon* upheld that "persons have a reasonable expectation of privacy in their property against drone surveillance, and therefore a governmental entity seeking to conduct drone surveillance must obtain a warrant or satisfy a traditional exception to the warrant requirement." The Long Lake Township hired a commercial drone pilot to capture aerial imagery of the Maxon's property to establish that the property was serving as an illegal salvage yard – violating a municipal zoning ordinance and creating a nuisance by breaching a previous settlement agreement. The Long Lake Township filed a civil action against the Maxon's, submitting drone photographs as evidence. The Maxon's successfully suppressed the drone photographs as a 4th Amendment violation. The courts made the distinction between the case of crewed aircraft surveillance in *Florida v. Riley* and the "low-altitude, unmanned, specifically-targeted drone surveillance of a private individual's property" as "qualitatively different from the kinds of human-operated law enforcement agency aircraft surveillance overflights permitted by Florida v. Riley”. Currently, 18 states have laws requiring state and local law enforcement agencies to acquire warrants before using drone technologies for evidence-gathering surveillance, and this case establishes precedent that drone surveillance constitutes a search under the 4th Amendment and requires a warrant (National Conference of State Legislatures, 2023).

California successfully amended its Civil Code section 1708.8 law as of January 1, 2016 as part of State Assembly Bill 2306. The law (1708.8) is colloquially referred to as California’s “paparazzi law”. The amendments address issues of aerial trespass by defining conditions for associated invasion of privacy by declaring that, “a person can be held liable for invasion of privacy by knowingly entering into the airspace of another person to capture a visual image of an individual engaging in a private, personal, or familiar activity.” The law effectively expands the reach of current state law by removing the condition requiring the use of a “visual or auditory enhancing device” and imposes liability if the operator uses any device, including a drone, in ways that a person with a reasonable expectation of privacy would find offensive. The law does not ban drone flight over private property, but it does set conditions for a plaintiff to pursue legal actions against a drone pilot based on the aircraft’s physical proximity and access to capture physical impressions of private spaces and personal associations.

*Glaser v. Mitchel* (2019) demonstrates the successful application of the 1708.8 statute. Two residential neighbors got into a disagreement after one neighbor (Glaser) hired a certified commercial drone pilot to capture images of trees on the other neighbor’s property (Mitchel) that they thought posed safety risks, obstructed the property’s scenic view, and reduced available light. Glaser filed a suit under a local tree ordinance designed to resolve disputes between private property owners relating to the resolution of sunlight or views lost due to tree growth (CA Civil § 1708.8, 2019), but only after hiring a drone pilot to take repeated drone images of trees inside Mitchel’s property and its adjacent curtilage. Glaser was warned by Mitchel that his home was also a place of business where he saw clients that had a reasonable expectation of privacy. Mitchel appealed to the view ordinance and claimed trespass and invasion of privacy for “investigative activities undertaken by the Glasers' drone experts occurred without permission and prior to seeking mediation required by the view ordinance". Glaser and the drone pilot were charged with invasion of privacy under the recent Assembly Bill No. 856 CH. 521, Amendment to Cal. Civ. Code § 1708.8(b) which holds a "person is liable for physical invasion of privacy when the person knowingly enters, or a person hires someone to enter, onto the land or into the airspace above the land of another person without permission in order to capture recordings of the plaintiff engaging in a private, personal or familial activity and the invasion occurs in a manner that is offensive to a reasonable person".

The California Civil Code § 1708.8(b) specifically addresses the need to communicate the intention of the drone, gain consent from property owners, and not operate the drone in a manner that is "offensive to a reasonable person". The state law does not preempt federal law, as it does not attempt to ban drone traffic over the navigable superadjacent airspace over private property. In California, drone operations can legally fly over private property, but pilots need to work to assess privacy concerns and take actions to ensure transparency of their actions and mitigate risks to privacy.

### 4.2.3 Regional Drone Legislation Trends

The current regulatory landscape for drones is continuing to develop with an emphasis on drafting state laws and local ordinances that protect communities, avoid federal preemption, and promote innovative drone application. Existing and emerging state laws and local ordinances are focused on three key areas that promote accountability while continuing to foster innovation. These include:

1. Exercising land use and zoning powers to regulate public areas where drones can take-off and land in ways that protect the interests of safety, public health, aesthetics, and the general welfare of its communities. States and municipalities are also using their authority to condition the steps that need to be taken to perform take-offs and landings through case-by-case permitting processes, zone-specific laws (e.g., curfews), and agency-wide legislation.

2. Amending existing laws on aerial trespass and invasions of privacy to include drone operation and the intention of its pilot (e.g., surveillance, voyeurism, harassment, negligence, recklessness) and a property owner's reasonable expectation of privacy.

3. Defining requirements for emergency services and law enforcement use of drones including air space priority for emergency response drones and warrant requirements for law enforcement actions.

These approaches enable state and local governments to make decisions about drone operations in their region that can promote commercial use while respecting the airspace rights of recreational pilots. Additionally, these foci serve as a foundation for making future decisions aimed at protecting individuals and property rights. A current challenge for state and local governments is readily communicating laws and ordinances to remote pilots and residents. The FAA encourages drone pilots to utilize the FAA B4UFLY app (`https://www.faa.gov/uas/getting_started/b4ufly`) which promotes accessible drone flight restrictions in national airspace, but this environment does not include all local rules and regulations that may impact a planned drone operation – like the ability to land and take-off from an area. The FAA has also created a "No Drone Zone" sign campaign to help state, local, territorial, or tribal government agencies communicate where pilots cannot operate UAS. The program's signage clearly delineates areas where take-off and landings are not permitted and references the relevant local ordinances (`https://www.faa.gov/uas/resources/community_engagement/no_drone_zone`).

### 4.2.4 Implications of a Status Quo Regulatory Future for Drones

Under the current regulatory framework, the FAA remains the agency responsible for regulating airspace safety and certifying commercial and recreational UAS pilots, while states and municipalities continue to enact laws that enforce drone trespass, invasion of privacy, and pilot negligence. The FAA will continue to provide testing for commercial and recreational remote pilot knowledge of rules and regulations protecting aviation safety. And, the agency will continue to develop outreach materials containing safety regulatory information and the new remote identification security requirements for drone and model aircraft operations accountability.

The scope of 'responsible operation' under the FAA only includes materials and outreach that warn UAS pilots to (1) comply with all state laws and local ordinances before flying over private property and (2) not use their UAS to conduct surveillance or capture images of persons in areas where there is an expectation of privacy without permission of the individuals. No additional training regarding best practices for mitigating risks to privacy will likely be included. The FAA continues to support its "No Drone Zone" physical signage program aimed at informing drone pilots about specific statutes and land use approval regulations. These 'No Drone Zone' signs do not restrict airspace authorization over an area, but they do limit authorization to take off or land from the property designated as a local No Drone Zone.

There are some benefits to the current approach from the state and federal perspectives. Under this scenario, the federal government would continue to be the primary regulator of UAS operations. The FAA brings a wealth of federal aviation safety standards that are well-developed, and freely available for study by prospective UAS pilots. And, the knowledge of these standards can be readily assessed through established federally approved aviation knowledge testing pathways. Additionally, the existing low financial cost of meeting federal remote pilot requirements would continue to attract workers to join the aviation workforce who might otherwise not have access to resources to engage in more extensive sUAS pilot training or pursue coursework to become a conventional airplane pilot.

From the states' perspective, drone privacy legislation is gaining momentum and establishing precedent in case law. States continue to enact laws defining actions that constitute an invasion of privacy, and civil and criminal lawsuits will shape future definitions of a reasonable expectation of privacy with respect to drones. Because the federal government is taking full responsibility for certifying remote pilots through its Part 107 knowledge-based exam, states will not bear the responsibility and costs for administering training programs and assessing sUAS pilot flight competencies.

However, this status quo approach presents some challenges for state and federal entities. First, the approach offers no opportunities for UAS pilots to receive training related to actual state or local regulations. Additionally, there are no opportunities to exercise the recommended best practices for protecting privacy, communicating with transparency, and acting responsibly in superadjacent airspace. It is plausible that increased commercial and recreational UAS traffic would also result in increased confrontations with concerned members of the public as the current approaches neglect to effectively communicate to landowners their property rights under contemporary aviation law. For example, a landowner who encounters a drone flying overhead may confront a remote pilot based entirely by the *ad coelum* maxim, but may be unaware of current state or local statutes protecting property owners from drone invasion of privacy, or may have little knowledge of what recourse they have to report a civil claim or file a criminal grievance. In these situations, it becomes the responsibility of a remote pilot to professionally communicate their intentions, qualifications, granted authority, while respecting the public's reasonable expectation of privacy.

### 4.2.5 Law Enforcement & Remote ID

It is also unclear how law enforcement will receive additional training to deter, detect, and investigate unsafe or unauthorized drone operations. Law enforcement officers called to investigate a civil complaint regarding drone activities will need to assess the underlying activity associated with a drone operation as there may also be additional violation (e.g., reckless endangerment, negligence, voyeurism, harassment, burglary, drug trafficking). While investigating a claim it may be unclear whether state and local law enforcement will be effective at enforcing drone regulations. Local law enforcement agencies cannot directly enforce federal regulations (i.e., Part 107 rules) but they can gather evidence (e.g., proof of aircraft registration and remote pilot certification, flight path and altitude, time of day, flying over people) and bring it to the attention of the appropriate federal regulatory agency (i.e., FAA, DHS, DOT) for enforcement action. In fact, the FAA has already developed an assistance and resource program called the Law Enforcement Assistance Program (LEAP) which provides training materials and points of contact for federal, state, local, tribal, and international law enforcement agencies working to address matters of organized crime, drug trafficking, criminal activity, and threats to national security using U.S. registered UAS aircraft and FAA certified remote pilots. The FAA will take the necessary regulatory enforcement actions when deemed appropriate and will provide the necessary aviation-related support to law enforcement agencies pursuing airborne smuggling interdiction and criminal prosecution.

Increased drone air traffic, coupled with current regulatory and certification frameworks, could result in escalating public confrontations, increased law enforcement engagement, and additional drone-related civil lawsuits. The resulting climate could lead to reduced public acceptance for drones and fewer applications for social good.

On January 15, 2021, the FAA established requirements for uncrewed aircraft to be equipped with remote identification (also called “Remote ID” or RID) to address safety, national security, and law enforcement concerns as UAS operations expand (14 CFR 89 § 44809, 2021). The remote ID regulations were developed to address public safety issues by increasing the transparency and accountability of UAS operations by providing a digital license plate for all uncrewed aircraft. In the U.S., crewed vehicles already have some form of remote identification. Crewed aircraft have onboard tracking systems called Automatic Dependent Surveillance-Broadcast (ADS-B). Maritime vessels have Automatic Identification Systems (AIS), and automobiles have license plates clearly displayed. Remote identification transmitters on uncrewed aircraft can support law enforcement and federal agency investigation of drones operating unsafely or in restricted areas. The RID security measure may not directly protect privacy rights but it could discourage irresponsible and illicit activities.

The RID rule was originally made effective on March 16, 2021 but was delayed until April 21, 2021, after concerns were raised during the Notice of Proposed Rulemaking (NPRM) about potential security risks associated with a network-based remote identification requirement (`https://www.federalregister.gov/`

d/2020-28948/p-180). The rule was revised to require a local broadcasting method and was delayed two more times in order for (1) RID and UAS manufacturers to design, develop, and test RID systems that met FAA and FCC regulatory requirement (September 16, 2022) and (2) allow uncrewed pilots the opportunity to meet the operating requirements (September 16, 2023). During the public comment period for the NPRM it was pointed out that the remote identification methods will "make pilot and aircraft identification easier for law enforcement, increase airspace safety, further protecting citizens' privacy". The FAA responded to public comments regarding the potential for remote ID to safeguard privacy agreeing with the "greater ability of law enforcement to locate the pilot" (https://www.federalregister.gov/d/2020-28948/p-226), but cautioned that the rule was "not promulgated for the purpose of addressing concerns about unmanned aircraft that violate privacy laws." (p. 226) (14 CFR 89 § 44809, 2021).

The Remote Identification of Unmanned Aircraft Systems (89 U.S.C. §44809) final rule offers three options for remote pilots to meet compliance including operating: with a standard remote ID (SID) built-in to newly produced UAS, retrofitting existing UAS and remote-controlled model aircraft with a broadcast remote ID (BMID), or operating without a remote ID in FAA-recognized identification areas (FRIA). FRIAs will be the only locations where recreational UAS and other remote-controlled aircraft exceeding 250 grams (0.55 lbs.) can operate without a remote ID solution. All uncrewed aircraft weighing under 250 grams and flown for recreational purposes are exempt from remote ID requirements. The sub-250 gram UAV limit is based entirely on safety guidelines, after determining that these aircraft are less likely to cause damage or injury than drones weighing more (49 U.S.C. § 44809). All commercially operated UAS will need to comply with broadcast remote ID solutions regardless of aircraft weight (49 U.S.C. §44809). Remote ID systems will broadcast a unique identifier for the drone aircraft, track drone position (i.e., timestamp, latitude, longitude, altitude, and velocity), identify the control station location (SID) or take-off location (BMID), and broadcast the aircraft's emergency response status (e.g., disaster relief, search and rescue missions, law enforcement investigations). Remote ID can increase remote pilot accountability as aircraft registration information and pilot location will be readily available to local law enforcement and concerned members of the public through open-source applications providing pathways for evidence gathering and intervention for UAS activities that violate state statutes (e.g., trespassing, invasion of privacy, stalking, harassment, private nuisance, assault). Ultimately, remote ID will likely do little to curtail invasions of privacy by recreational pilots operating UAV that are under the 250g weight requirement and exempt from for remote ID compliance.

Commercial UAS operations will need to comply with remote ID regulations on all drones regardless of their weight and it is likely that remote ID will have a small financial impact on this sector, because regulations will require that all drones over a weight of 250g designed and manufactured after the remote ID final rule to have SID technology already integrated into aircraft. The remote ID final rule (49 U.S.C. §44809) also requires that existing commercial UAS aircraft manufactured prior to regulation be retrofitted with dedicated BMID transmitters assigned to each aircraft. The inability to transfer BMID transmitters between commercially registered aircraft increases the material cost, maintenance labor, or replacement cost of non-compliant aircraft for commercial operations with multiple aircraft. Recreationalists will be able to transfer BMID transmitters between aircraft. Estimated cost for BMID transmitters vary between \$120 - \$300.

Recreationalists and educators have raised concern about the availability of FRIA sites to meet the growing interest in UAS flight. Only FAA-recognized Community-Based Organizations (CBOs) and educational institutions are eligible to request the establishment of a FRIA. As of April 1, 2023, there are only 233 registered Recreational Flyer Fixed Sites in the U.S. sponsored by 501c(3) Community-Based Organizations (CBOs) that will automatically qualify as FRIA sites (`https://udds-faa.opendata.arcgis.com/`) and the FAA announced that it could not provide an estimated timeline for FRIA application approvals. The AMA has begun the process of requesting FAA-Recognized Identification Areas (FRIA) on behalf of its chartered aviation clubs but many of these clubs traditionally support fixed-wing (airplane) type flight. The unique maneuvering capability of single-rotor (remote-controlled helicopter) and multirotor quadcopters (UAS) poses challenges for air traffic at many of these exclusively fixed-wing (airplane, glider) sites. In response, new recreational aviation CBOs have emerged with the goal of securing FRIA sites with a special focus on supporting multi-rotor (UAS) aircraft and the growing number of sponsored first-person view (FPV) drone racing and drone education events (See `https://www.multigp.com`, Collegiate Drone Racing Association `https://cdra.net/`, FPV freedom coalition (FPVFC), Flite Test Community Association (FTCA)).

Some UAS recreationalists, predominantly from the FPV UAS community, have opposed the new remote ID regulations and even pursued legal actions challenging the constitutionality and legality of the FAA's final rule. In 2021, Tyler Brennan (CEO, Race Day Quads) filed a petition for review in the United States Court of Appeals for the District of Columbia Circuit (*RaceDayQuads, LLC v. FAA*, 2021) on the grounds that the Remote ID requirement (1) amounts to constant, warrantless governmental surveillance of a property owners curtilage in violation of the Fourth Amendment, (2) infringes on the privacy interests of sUAS operators, (3) violates First Amendment protections by requiring individuals to associate with a private dues-collecting organization (CBO) in order to exercise privilege in the public airspace. His request for vacatur of the FAA rule failed with the court's judgment that nearly all UAS operate in public airspace and the requirement to broadcast a drone's location and the location of its operator while aloft in the national airspace does not violate a reasonable expectation of privacy. Brennan's petition was unsuccessful but it did act as catalyst to organize the FPV UAS recreational community. The recreational drone community has formed its own representative 501(c)(3) organization, the FPV Freedom Coalition (FPVFC)) that actively participates in the FAA Drone Advisory Committee (DAC) (now Advanced Aviation Advisory Committee (AAAC)) Tasking Group, the Beyond Visual Line of Sight Aviation Rulemaking Committee (BVLOS ARC) (FAA, 2021).

## 4.3 Discussion

The current U.S. regulatory frameworks for the integration of drones into the national airspace are an evolving landscape of federal regulations ensuring flight safety, coupled with emerging state and local legislation restricting drone use in order to protect property and privacy rights. The federal standards set clear operational rules and regulations for drone flight operation and an attainable assessment pathway for certifying that pilots meet the minimum knowledge standards to operate a drone safely in the national airspace. The federal written examination approaches to knowledge assessment are sufficient for assessing commercial (Part 107) and recreational (TRUST) drone pilots' knowledge and provide an enforcement mechanism for revoking the privileges of pilots violating accepted safety standards. Although enforcement of safety and security violations has been challenging, new regulations requiring remote identification can increase the transparency of drone operations and support law enforcement and other federal agencies as they work to investigate unsafe or unauthorized actions. Remote identification also provides an affordable and accessible foundation for increasing the safety and security needed for more complex drone operations. States have successfully worked in consultation with the FAA to design clear legislation that is not preemptive of federal statutes and reflects the reasonable expectations of privacy for its residents. In many cases, states have successfully amended existing laws related to recklessness, negligence, voyeurism, harassment, and set attainable operational requirements for continued use of drone technology by public safety agencies. States have also agreed to set preemptive clauses that prevent local jurisdictions from setting operational UAS restrictions regulating navigable airspace without first consulting with state and federal entities.

Federal, state, and local entities have successfully enacted legislation regulating drones within their respective jurisdictions, but each has its own unique challenges. In the federal arena continued efforts are needed to resolve technological and logistical challenges with the design, distribution, and compliance of remote identification technology. Additionally, outreach efforts have informed drone pilots of pending requirements but little has been done to inform the public at large about remote identification technology and how one can gather information and report unsafe or unauthorized activities to the appropriate authorities. It also remains unclear how law enforcement agencies will be equipped to handle civil complaints and investigations of drone pilots endangering the safety, security, or privacy of people within the vicinity. Additionally, the federal written exam adequately assesses pilots' aviation knowledge but a key component of flight safety training and assessment for other forms of crewed flight involve a standardized evaluation of operational flight proficiency. Crewed aircraft pilots are certified based on their ability to demonstrate aeronautical knowledge and complete flight operational tasks required for the specific type of pilot rating (e.g., recreational/sport, private, commercial). Accepted standards for assessing the safe operation of drone aircraft have been developed by agencies (i.e, NIST) and organizations (i.e, ASTM) but no assessment requirements have been developed by the FAA to evaluate drone pilots' aircraft maneuvering proficiency.

State and local jurisdictions have successfully enacted laws restricting drone operation based on zoning and land use standards and defined drone pilot actions that can be considered an invasion of privacy. But this requires that drone pilots be increasingly knowledgeable of changes in their privileges, respectful of the rights and concerns of others, and compliant with ground-based operational restrictions. The most readily available resources for current state and local regulations are available on a variety of commercial training websites (e.g. `https://www.thedroneu.com/`, `https://uavcoach.com/drone-laws/`) and a volunteer-based group "Drone Laws for a Safer Airspace" (`https://drone-laws.com/usa-drone-laws-in-usa/`) but the quality of information available at each vary substantially. A centralized searchable resource for reliable information on local and state drone regulations would be a powerful flight planning tool for drone pilots. The FAA has recently partnered with Aloft© to host a revised version of its free-of-charge B4UFLY map app. The B4UFLY app offers a simple and easy way for U.S. drone operators, both recreational and commercial, to check airspace and ground-based restrictions before taking flight and post their flight status for others to see on the map. The app has already successfully integrated several local, state, and federal restrictions as mapped spatial boundaries with links to additional information from federal, state, and local websites. The application could also add links to relevant state laws or ordinances in the supporting information window to help inform drone pilots of current statutes. And, B4UFLY is already part of a larger education campaign (`https://knowbeforeyoufly.org/`) organized by the Academy of Model

Aeronautics (AMA), the Association for Uncrewed Vehicle Systems International (AUVSI), and the Consumer Technology Association (CTA) in partnership with the Federal Aviation Administration (FAA) to provide "prospective users with the information and guidance they need to fly safely and responsibly."

The landscape of U.S. federal and state civil drone laws, regulations, and policies remains dynamic, with federal-state tension regarding the development of privacy legislation. There is a significant need for civil drone pilots to demonstrate an understanding of federal safety regulations and state privacy laws.

Although the current federal certification framework assesses the remote pilot's knowledge of what is needed to fly safely and legally, there are no training curricula that equip drone pilots with an accepted pilot code of ethics or assesses knowledge of the application of community best practices.

Expanding professional certification beyond the federal UAS Part 107 remote pilot certification program to support professional standards and training across the jurisdictions of federal and state governments, could be achieved through existing commercial and collegiate education affiliations. In the next chapter I examine the usefulness of a commercial pilot training and certification solution for addressing growing safety and privacy concerns, and identify the potential benefits and challenges of the approach.

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# Chapter 5

# Towards a Code of Ethics and Best Practices for Teaching About Privacy Concerns in Drone Pilot Certifications

> Our ability to film nearly anything has outpaced our ability to think clearly about what we can and should do with the footage.
>
> \- Alex Wild (2015). Scientific American

## 5.1 Introduction

Persistent federal-state tension regarding privacy legislation points to the need for drone pilots to demonstrate an understanding of federal safety regulations and state privacy laws (Chapter 3). The current federal certification framework evaluates pilots' knowledge of safe and legal flying, but lacks training on ethics and drone pilot best practices. Expanding professional certification beyond the federal program can support standards and training across federal and state jurisdictions. In this chapter, Here, I examine how non-profit organizations can provide an accredited certification for commercial pilot training solution that assesses safety and privacy concerns. I also explore how such a certification can be administered through existing commercial and higher-education collaborations.

There is currently no federal requirement to complete a certified training program to become a commercial drone pilot. An individual only needs to acquire the Part 107 study materials, study, and pass the FAA's Part 107 knowledge exam with a score of 70% or more correct (14 C.F.R. § 107). Once Part 107 certified, a remote pilot can operate commercially in the U.S. as long as they do not violate federal safety regulations. For example, if a recreational or commercial drone pilot violates state or local statutes related to privacy invasion, they can be sued in civil court by parties filing claims under tort law – a process that can be burdensome for private citizens but that can be relieved equitability through civil fines and restraining orders. However, there would be no recourse for a plaintiff to pursue actions against a remote pilot's federal certification based on violations of state statutes unless the pilot has specifically violated federal rules and regulations related to safety. In contrast, if local law enforcement or concerned members of the public report a drone operator to the FAA for unsafe or unauthorized operation within the national airspace, the FAA's Compliance and Enforcement Program will then investigate via its Flight Standards District Office (FSDO), possibly resulting in civil penalties, criminal prosecution, and actions against an operator's FAA-issued certificate (Order 2150.3C, 2018).

Technical professions typically require certifications that offer baseline training, certification, and continuing education to remain up-to-date on technological advances, regulatory developments, and professional best practices. These professional certifications can be granted based on work portfolios, competency exams, or coursework achievement and typically adhere to standards designed by certificate accreditation programs. These certificate accreditation programs are typically granted by organizations that publish production and testing standards for various industries. Examples of internationally recognized standards organizations and their associated certificate accrediting bodies include:

- American National Standards Institute (ANSI):
  - National Accreditation Board (ANAB)
- National Institute of Standards and Technology (NIST):
  - National Voluntary Laboratory Accreditation Program (NVLAP)
- International Organization for Standardization (ISO):
  - International Laboratory Accreditation Cooperation (ILAC)

ASTM International is a leading developer of voluntary standards in the U.S. system. ASTM International is also accredited by the International Accreditors for Continuing Education and Training (IACET) and complies with the ANSI/IACET internationally recognized standards of excellence in instructional practices. ANSI administratively serves as a neutral-facilitator and coordinator of the United States private-sector voluntary standardization system for defining standardization needs for emerging technologies at national and global scales. In September 2017, ANSI launched the Unmanned Aircraft Systems Standardization Collaborative (UASSC) with the goal of fostering collaboration between UAS regulatory authorities, industry entities, research and development, and standards developing organizations (SDOs). The UASSC was not established to coordinate the development of standards and compliance assessment programs necessary for the safe and responsible integration of UAS into U.S. national airspace but it did successfully facilitate the accelerated development of a “Standardization Roadmap for Unmanned Aircraft Systems” (ANSI Version 2.0, June 2020) which outlines future UAS standardization approaches for civil, commercial, and public safety applications. ANSI also administers a Certificate Program (ANSI-CAP) which assesses and accredits certificate granting organizations that conform to standards of ANSI/ASTM E-2659 and the ASTM UAS training standards for public safety remote pilots (ASTM F3379, ASTM F2908, ASTM F2910, ASTM F3266, ASTM F3330). These standards developed by ASTM International's Unmanned Aircraft Systems (UAS) Committee F38 are ideal for public safety offices and law enforcement agencies and outline knowledge and skills that are transferable to a variety of other professions that are utilizing drones.

An accreditation audit process of the organization's certificate program is used to evaluate compliance with accepted standards for instructional design, valid and reliable assessment of learning outcomes, and a system for monitoring and managing the application of the certificate. Additionally, the accreditation standard also evaluates the certifying organizations' structure, administration, policies and procedures, and records systems.

As demand for proficient and responsible UAS pilots continues to grow, the Association for Uncrewed Vehicle Systems International (AUVSI) has been working with regulators, industry, and educational institutions as part of the ANSI-UASSC collective to establish a industry accepted certification for commercial UAS pilots and UAS service provider organizations. The AUVSI is the largest international non-profit trade association dedicated to the advancement of uncrewed systems and robotics (`AUVSI.org`). The organization represents corporations and professionals from over 60 countries with its members actively working with uncrewed systems across civil, commercial, and defense sectors. The AUVSI currently has a NIST/ASTM-compliant training and certification program called the Trusted Operator Program$^{\text{TM}}$ (TOP) developed in collaboration with Embry-Riddle Aeronautical University and ANSI's UASSC Standardization Roadmap for Unmanned Aircraft Systems initiative. AUVSI TOP is a professional UAS community initiative designed to communicate industry best practices and to set an expected professional code of conduct for commercial drone pilots. The TOP approach creates standardized policies, training procedures, and certification requirements for individuals and organizations operating as commercial remote pilots and UAS service providers. The program also evaluates competencies of individual remote pilots and the UAS service provider organizations using the current NIST/ASTM testing standards. TOP individuals and organizations are assessed and audited routinely guided by ANSI standards and implemented by TOP certifying bodies that specialize in a particular field of UAS application. TOP protocols can be amended based on the applications and emerging regulations for UAS operations by commercial entities, state and government agencies in the U.S. and internationally. For example, the AUVSI TOP "Protocol Certification Manual" contains a "Functional Area Performance Measures for Public Safety Operators" (p.44) with training and auditing that addresses several components aligning with the NTIA's "Voluntary Best Practices for UAS Privacy, Transparency, and Accountability" (NTIA, 2016) and the University Aviation Association's "UAS Pilot Code". In 2018, the University Aviation Association (UAA) worked collaboratively with crewed aviation and UAS professionals as part of its Aviators Code Initiative (ACI) to develop a UAS Pilots Code (UASPC). The UASPC was written as a voluntary aspirational code of conduct that sets agreed values-based guidelines and recommended practices for UAS pilots and UAS organizations. The UAA's UASPC has the potential to serve as a guiding document for curricular design that addresses safety, security, privacy, professionalism (Baum et al., 2018). The University Aviation Association has also been working collaboratively as part of the ANSI UASSC collective to standards for assessing compliance with the guiding UASPC.

Most notable in the UASPC is the recommended privacy practices that can serve as a guide for UAS pilots as they work in the superadjacent public airspace. Section IV. Security and Privacy, Part e of the UASPC outlines practices to "recognize and respect the public's reasonable expectation of privacy" and integrates components of the NTIA voluntary best practices with the addition of clear articulations for motivation for these practices. For example, the UAA's UASPC provides clear suggested practices for protecting PII by (1) "limiting data capture to mission-related objectives.", (2) "retain personal data only when legally and purposefully collected, and only for the duration necessary.", (3) avoid the collection of personal data without the subject's consent", and (4) "delete such data immediately upon discovery, and maintain a de-identified log of the deletion." In addition to the recommendation to adhere to informational privacy best practices the UASPC also makes recommendations for reducing the chilling effect of drone operations. These include working to: (1) "understand and respect the public's reasonable expectation of privacy rights of others by conducting your UAS operations with prudence and restraint", (2) "seek to avoid even the appearance of impropriety regarding potential violations of privacy with your operations", (3) "recognize that limited societal experience may cause some people to consider unmanned aircraft harassing, invasive, or threatening", (4) "respond with courtesy and professionalism", and (5) "implement a written privacy policy that is appropriate and responsive to your UAS operations".

In the TOP protocols developed by AUVSI there is an emphasis on having developed policies that address constitutional provisions and applicable laws and regulations safeguarding individuals' rights to privacy, civil rights, and civil liberties. These AUVSI – TOP privacy protocols require that organizations conduct a documented assessment of UAS technology impacts and develop a usage policy that addresses community privacy concerns. The goal of this assessment is to identify practices that will minimize the collection and storage of personally identifiable information (PII), and create clear pathways for engaging transparently with the public regarding privacy concerns or complaints. Additionally, all AUVSI TOP certified remote pilots are invited to voluntarily pledge to abide by a professional code of conduct that specifically includes: "(1) complying with all federal, state, and local laws, ordinances, covenants, and restrictions, including privacy, nuisance and trespassing and (2) be respectful and responsive to the needs of the public and environment."

## 5.2 Commercial Certification Pathways

There are numerous commercial programs aimed at preparing prospective remote pilots for the Part 107 exam, but the curricular focus tends to be entirely on written test preparation and only assessing knowledge of federal safety regulations. The majority of these test preparation organizations are not accredited by a governing organization that ensure learning objectives align with accepted standards for the profession. Professionals participating in many of these commercial programs receive no hands-on experience with the safe and responsible operation of UAS or introductions to a UAS pilot code of conduct. However, there are a number of emerging commercial education programs that have integrated hands-on pilot proficiency training and testing, and instruction on ethical best practices for protecting privacy into their programs through collaboration with professional certifying organizations (Table 5.1).

Table 5.1: Aviation organizations and affiliated drone education initiatives

| Organization | Affiliation | Mission / Focus | Education Initiatives |
|---|---|---|---|
| Academy of Model Aeronautics (AMA) (1936) 501(c)(3) | U.S. nationwide organization of clubs providing flying fields and club sponsored learning events that promote safety and recreation for model aircraft enthusiasts. Led by Jenny Rosenberg, former Department of Transportation Acting Assistant Secretary for Aviation and International Affairs, the group's focus is on legislative and regulatory activity | World-class association of modelers organized for the purpose of promotion, development, education, advancement, and safeguarding of model (e.g., small-scale remotely operated) aviation activities. The Academy provides leadership, organization, competition, communication, protection, representation, recognition, education, and scientific/technical development to modelers. | Well-established outreach, competitions, education grants, and hands-on programs hosted by recreational flight clubs. Partnered with drone racing MultiGP Stem Alliance and "Drones In School - STEAM Program" and FAA knowbeforeyoufly.org and Aloft B4Ufly.org. Sponsors "Drone Safety Day Events" to promote FAA TRUST certification |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
|---|---|---|---|
| Association for Uncrewed Vehicle Systems International (AUVSI) (1972) Nonprofit 501(c)(3) | Based in Arlington, Virginia, USA. Largest global non-profit dedicated to advancement of uncrewed systems and robotics — represents professionals in 60 countries from industry, government, and academia. Members work in the defense, civil and commercial markets. | Focused on supporting remote autonomous systems industry through policy development and expanded operation of uncrewed systems. | RoboNation (formerly, AUVSI Foundation). Partner with AMA and FAA's knowbeforeyoufly.org. Launched Trusted Operator (TOP) certification (2018). AUVSI-TOP participating with ANSI-CAP - ANSI Unmanned Aircraft Systems Standardization Collaborative (UASSC). Embry-Riddle Aeronautical University developed TOP standards. Praxis Aerospace Concepts International, Inc. – TOP certifying body. |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
|---|---|---|---|
| Airborne Public Safety Association (APSA) (1968) 501(c)(3) | Based in Frederick, Maryland, USA. International organization, individual membership from Air Support Units and Public Safety Agencies. | Supports public safety professionals by advancing safe and effective use of crewed and uncrewed aircraft by governmental agencies in support of public safety operations through training, collaboration, advocacy, and educational programs. | Offers aviation accreditation and standards compliance services through its Aviation Unit Accreditation services (APSAC) focused on compliance with safety training standards. Works in conjunction with DRONERESPONDERS and National Fire Protection Association to implement NIST and ASTM sUAS Standard Proficiency Testing |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
| --- | --- | --- | --- |
| American Society for Photogrammetry and Remote Sensing (ASPRS) (1934) 501(c)(3) | 7,000 professional international members. Accreditation from the Council of Engineering and Scientific Specialty Boards (CESB). | Advances knowledge and skills in mapping sciences and promotes the responsible applications of photogrammetry, remote sensing, geographic information systems (GIS) and supporting technologies. | ASPRS offers two certifications at two different levels, Mapping Scientist and Technologist with specialty areas of Photogrammetry, Remote Sensing, GIS, Lidar, and UAS. Certifications are based on degree-attainment, industry engagement, professional experience |
| Consortiq™ (2015) Commercial Education | Based in Annapolis, Maryland, USA and Heathrow Airport, London. Authorized training AUVSI-TOP program training in Europe and North America. . | Training and consultation meeting international standard. Coursework includes U.S. FAA Part 107 prep and UK's A2 CofC and GVC test training, and drone educator training. | Fee-based "Train-the-Trainer Drone Integration" AUVSI-TOP training and consultation |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
| --- | --- | --- | --- |
| DARTDrones ©, LLC (2014) Commercial Education | Based in Utah, USA offers training in over 25 US cities including: Part 107 test prep, advanced industry training, and UAS implementation consulting services. AUVSI TOP certified instructors | Provides commercial and public safety professional drone training, consultation, and expert support in operations and analytical workflows. | Lauched drone programs for young learners (K-12), college, and workforce development institutions. Offers DARTdrones Public Safety Grant for full or partial funding to departments nationally for 107 preparation and flight planning an operation. |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
|---|---|---|---|
| Drone U ™ (2014) Commercial Education | Based in Loveland, Colorado, USA. Offers online asynchronous Part 107 exam preparation, modules on flying techniques, business applications, and legalities. Also offers in-person hands-on flight training and data processing workshops. | Provides knowledge-based education resources for UAS and crewed airplane federal test-preparation, established in-person training courses focused on skills for commercial sector. | Hosts certified FAA TRUST online testing portal. |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
|---|---|---|---|
| DRONERESPONDERS (2017) 501(c)(3) | Based in Miami, Florida, USA. Coordinates Drones for Good™ and Airborne International Response Team (AIRT), Inc., providing airborne capabilities that help people prepare for, respond to, and recover from complex emergencies and major disasters. Fasted growing nonprofit advancing public safety UAS. | Unites aerial first responders, emergency managers, and search and rescue specialists to help learn, train, and test with objective of maximizing drone operations for public safety. Volunteers bridge gaps between government, industry, and academia. | AIRT-TF-1 Mobilizes volunteer-based deployable resources for UAS, GIS, and emergency management. Members are trained and highly-experienced UAS public safety, law enforcement, fire rescue, emergency management, critical infrastructure, and security personnel. Utilizes Pilot Institute™ for continuing education credits. |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
|---|---|---|---|
| Federal Aviation Administration (FAA) (1958) | Federal Agency within the U.S. Department of Transportation. Financed from the Airport & Airway Trust Fund appropriated thorough Reauthorization Act. | Federal leadership in planning, developing safe and efficient national airport system. | Since 1935, partnered with National Education Association to define and promote aviation education as Aviation & Space Education (AVSED) program hosting Aviation Career Education Academy. FAASTeam offers national safety promotion initiatives, national policy, and guidance. The Unmanned Aircraft Systems Collegiate Training Initiative (UAS-CTI) is recognizes universities, colleges, and technical schools preparing students for UAS careers. |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
|---|---|---|---|
| Influential DRONES®, LLC (2017) Commercial Education | Based in Marlto, New Jersey, USA. Specializes in aerial services, training, consulting and equipment sales. Commercially supplies drones, counter-UAS equipment, and software. | Provides knowledge-based education resources for UAS and crewed airplane federal test-preparation, established in-person training courses focused on skills for commercial sector. | APSA Approved Proctor for the NIST sUAS Standard Test. Nationally recognized as an affiliate Industry Member with the FAA Safety Team (FAAST) program. |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
|---|---|---|---|
| Pilot Institute™ (2018) Commercial Education | Headquartered in Prescott, Arizona, USA. Online asynchronous knowledge-based courses for Part 107 exam preparation, drone hardware and software introductions, commercial business development, modeling and surveying, cinematography, public safety COA knowledge training. | UAS and crewed airplane federal test-preparation and related continuing education credits. currently developing in-person training network aimed at supporting public safety professionals and other commercial applications. | Accredited by the International Accreditors for Continuing Education and Training (IACET) and offers Continuing Education Units (CEUs). Partnered with DRONERESPONDERS to provide Public-Safety specific Part 107 and flight proficiency training using NIST standards. Hosts certified FAA TRUST Online Testing portal. |

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| Organization | Affiliation | Mission / Focus | Education Initiatives |
|---|---|---|---|
| University Aviation Association (1947) 501(c)(3) | Headquartered in Millington-Memphis Airport, in Millington, Tennessee, USA. Originally the National Association of University Administrators of Aviation Education. UAA is now comprised of over 1200 leadership members from more than 220 colleges and universities in the U.S., Canada, Australia, Europe, and Asia. | Policy and advocacy group for collegiate aviation. Instrumental in the advancement of degree-granting aviation programs. Provides voluntary independent program review for collegiate education programs. | Created Aviators Model Code of Conduct Initiative - UAS Pilot Code, Provides Aviation Student Scholarships, Mentoring Programs, Hosts Community Events - Annual Collegiate Aviation Education Conference & Expo, Aviation Policy Seminar for Students & Faculty |

In 2020, the U.S. Department of Commerce's - National Institute of Standards and Technology (NIST) developed a sUAS Standard Test as a reproducible method to objectively evaluate and measure proficiency and control of UAS aircraft (NIST, 2023). The NIST Standard Test was developed in collaboration with the ASTM International Standards Committee on Homeland Security Applications and was originally designed to evaluate the proficiency of public safety agency pilots' (e.g., fire, law enforcement, paramedics, search and rescue) use of aerial robots. NIST/ASTM sUAS evaluation standard includes ten aerial test methods that quantitatively measures the system capabilities of the drone and the proficiency of the pilot in carrying out five basic maneuvers including: accurate landing, vertical climbing, straight flight path, and level aircraft flight. The evaluation also assesses five functionality test methods, including maneuvering in circular orbits to visually identify objects from a distance and spiral maneuvers to conduct close-range inspections. Although the NIST/ASTM testing standards for pilot proficiency are originally tailored towards emergency responder and law enforcement training, UAS educators are adopting the NIST/ASTM protocols as an affordable and standardized method of assessing pilot proficiency. The widening adoption of NIST sUAS standards for operational proficiency has motivated commercial training organizations to offer hands-on drone maneuver training, proficiency assessment and certification (e.g., Consortiq™, Pilot Institute™, DARTDrones ©, LLC, Drone U ™, Influential DRONES®, Praxis Aerospace Concepts International, Inc.).

The Pilot Institute™ commercial online drone education program, is unique in being the only online drone aviation education program to be accredited by the International Accreditors for Continuing Education and Training (IACET) and the U.S. Department of Education offering Continuing Education Credits (CEUs) that comply with American National Standards Institute (ANSI) standards (IACET, 2021). The Pilot Institute™ has also partnered with DRONERESPONDERS to provide Public-Safety specific Part 107 knowledge training and CEUs for public safety, law enforcement, fire rescue, emergency management, critical infrastructure, and security personnel. DRONERESPONDERS is one of the fasted growing nonprofit 501(c)(3) organizations providing drone capabilities that help people prepare for, respond to, and recover from complex emergencies and major disasters. Together these two organizations are currently working to develop hands-on workshops and assessments for UAS operational proficiency that are affordable to public safety agencies, meet NIST/ASTM drone flight proficiency assessment standards and align with the Airborne Public Safety Association (APSA) standards for test proctoring (C. Werner – Director DRONERESPONDERS Public Safety Alliance, personal communication, 4/29/2023).

Consortiq™ has successfully utilized AUVSI TOP privacy and security protocols to train commercial drone pilots in the United Kingdom and European Union. Consortiq™ has AUVSI TOP certified educators that train EU drone pilots and service providers in accordance with the voluntary guidelines outlined in Article 40 of the General Data Protection Regulation (GDPR) – Code of Conduct which encourages a privacy impact assessment as part of drone operator and drone pilot professional commercial activities. The amenability of AUVSI TOP protocols has allowed Consortiq™ to adapt training approaches that address requirements from the EU's GDPR privacy guidelines.

In the U.S., commercial education organizations with AUVSI TOP-certified instructors have successfully provided training and certifications that collectively meet an agreed set of standards for remote pilot knowledge, operational skills proficiency, and professional conduct. This process moves pilot training beyond the minimal prescriptive requirements assessing knowledge of federal operating regulations to a training paradigm that assesses a level of knowledge, flight proficiency, safety and risk management, and professionalism required by employers and clients of commercial UAS operators. For example, DARTDrones ©, LLC is a U.S. based AUVSI TOP certified training provider that introduces the AUVSI TOP proficiency assessments and pilot code of conduct as part of its training protocols. Additionally, DARTDrones offers a U.S. Public Safety Grant providing funding towards drone training for police and fire departments seeking to integrate drones into their organization that may not have the resources needed to pursue TOP training for their organization. The DARTDrones Public Safety Grant provides full or partial funding to accepted departments nationwide and to date the organization has awarded over $500,000 in drone training grant funds to over 237 police and fire departments (DARTdrones LLC©, 2023).

Another viable option would also be for commercial drone education organizations to adopt the same standards used by AUVSI in the design of its Trusted Operator Program (TOP) by creating hands-on opportunities for training and assessing NIST/ASTM UAS flight proficiency standards, design modules introducing a pilot code of conduct (e.g. UAA UASPC, NTIA Voluntary Best-Practices), and pursue accreditation to support continuing education units for professionals, like the Pilot Institute™. Although the adopted standards would be similar to the AUVSI TOP certification, such an approach would lack the auditing process of a certifying organization and could lead to compliance drift over time. Certifications offered through a centralized accrediting organization have value for demonstrating foundational knowledge, operational proficiency, and a willingness for operations and individuals to commit to training and standards in their profession. Demonstrating a level of competency by participating in certification processes not only adds credibility to individuals but sets a standard among professionals in a field (Adams et al., 2004).

However, the intangible qualities of a competent and responsible drone pilot or drone training organization cannot entirely be captured by completing a certification program. Although certifications demonstrate a willingness to invest in professional development and the advancement of the profession through continuing education and participation, client trust is typically gained over time from service providers that are associated with a centralized certifying body (e.g., ANSI) that can substantiate professional qualifications, endorse training quality, and ensure adherence to standards of practice that increase the credibility of a profession.

Drone pilots are a unique class of aviator, operating aircraft from the ground and controlling them exclusively within the superadjacent airspace. Operating in close proximity to public and and private spaces requires a distinct set of social and technical skills. These include the ability to make sound decisions while under social pressures, maintain heightened situational awareness of aerial and ground activity, possess effective leadership and communication skills, exhibit humility, resilience, and uphold a professional code of practice. Sound decision-making is crucial for all types of aviators. A drone pilot must be able to swiftly and effectively make judgments in response to rapidly changing social and environmental conditions. They must evaluate factors such as weather conditions, aircraft performance, and safety hazards, while addressing inquiries or concerns from bystanders. To facilitate sound decision-making, drone pilots must maintain a clear and heightened sense of situational awareness, proactively monitoring their surroundings for potential aerial and ground hazards. Additionally, drone pilots need to demonstrate leadership capacity by communicating clearly and assertively with crew members, the public, and clients in ways that inspires confidence and trust. These leadership capacities are best practiced when pilots are able to maintain resilience, humility, and an unwavering commitment to ongoing learning, regardless of their level of expertise. Resilience entails being open to feedback, acknowledging mistakes, and continuously strive to improve skills and knowledge, and recovering from setbacks and challenging experiences. Resilience is crucial when adjusting to different aircraft, unfamiliar environments, and navigating complex social interactions. Lastly, a drone pilot must maintain a commitment to a professional code of practice that ensures safety, safeguards security, and respects the privacy concerns of others. By upholding professional standards, drone pilots contribute to the well-being of others and the continued advancement of drone-based applications.

## 5.3 Components of Curricular Framework

A drone operations training curriculum should aim to provide students with the necessary knowledge and skills to become proficient and responsible drone pilots. The curriculum needs to focus on developing technical flight proficiency skills, risk assessment abilities, and ethical considerations. The training program should integrate both theoretical knowledge and practical application through project-based flight missions and collaborative team exercises. This can be achieved with a curricular framework that includes the following four components.

1. Knowledge Preparation - Part 107 Training
   Students receive comprehensive training in accordance with the Federal Aviation Administration (FAA) rules and regulations for commercial drone

pilots. Students are introduced to the rules and regulations, airspace classification types, influential weather factors, emergency procedures, and best-practices for operating drones safely and legally. Throughout the training students have the opportunity to check their understanding and prepare to successfully complete the Part 107 exam and obtain their commercial remote pilot certificate.

2. Project-Based Flight Missions
   Students engage in a series of project-based flight missions to apply their skills in various real-world scenarios. These missions include mapping, cinematic filming, and 3D scanning, allowing students to gain hands-on experience with a variety of drone technology applications. These project-based missions enhance students' ability to flight plan, operate aircraft, and develop data collection and processing skills. Students work collaboratively in teams to plan flight missions and assess potential risks to safety, security, and privacy. They learn to identify and analyze potential hazards and develop risk mitigation strategies. This component emphasizes effective teamwork, communication, and decision-making skills in drone operations.

3. Transparency and Impact Reduction
   In conjunction with project-based flight missions students explore the ethical and legal considerations associated with drone operations. They develop actionable practices to increase transparency and reduce the impacts of their drone operations on safety, security, and privacy. This component encourages students to consider the public perception of drones and develop strategies to address concerns and build trust within the community.

4. Drone Pilot Ethical Code Development
   After engaging in project flight missions, students work in teams to develop their own set of best practices for reducing safety risks, maintaining security, and respecting privacy in drone operations. They compare their practices with established guidelines such as the UAA's

UAS Pilots Code and the National Telecommunications and Information Administration (NTIA) recommended best practices. Students can modify their own code or suggest additions to the existing guidelines based on their analysis and insights. To evaluate the students' understanding and application of the UAS pilot's code and best practices, they are presented with a variety of hypothetical flight mission scenarios. Students apply their newly formed code and demonstrate their ability to make informed decisions, prioritize safety, and address security and privacy concerns effectively. These scenarios could also be adapted into role-playing activities that simulate challenging situations encouraging students to practice effective communication, problem-solving, and decision-making skills.

Integrating intangibles such as ethics, teamwork, and decision-making skills into training programs is a crucial part of developing well-rounded and responsible drone operators. These intangible qualities can be incorporated into training curriculum through actual flight missions and scenario-based exercises that require students to work collaboratively to consider the potential impacts of their missions and make ethical decisions about their actions. By incorporating these elements, the training program ensures that students not only gain technical expertise but also develop a strong foundation in ethics, teamwork, and critical thinking, enabling them to navigate the complex landscape of drone operations responsibly and professionally.

## 5.4 Higher Education Certification Pathways

Higher education institutions have successfully formed partnerships and agreements with accredited non-profit organizations to provide recreational and professional certifications, at their campuses or affiliated commercial training centers. The National Association of Underwater Instructors (NAUI) is well known for its scuba diving education and certification programs (`https://www.naui.org/`). These collaborations can allow students to complete their scuba diving training and certification through NAUI-accredited centers while still earning academic credit toward their degree programs. NAUI recreational and professional certifications are integrated into existing college programs and coursework reducing tuition costs for students. The certifications are often recognized for academic credit or as part of specific programs and professional development.

A professional competency-based and curriculum-based certification pathway for training UAS remote pilots is being fostered by AUVSI from existing partnerships between the federal regulatory agency (FAA) and post-secondary institutions accredited by agencies recognized by the U.S. Secretary of Education. AUVSI has begun to leverage the FAA's extensive growing membership in the UAS College Training Initiative (UAS-CTI) to support continued adoption of the Trusted Operator Program certification into institutions of higher-education.

The UAS-CTI recognizes accredited post-secondary institutions (i.e., technical schools, colleges, universities) that prepare students for careers in UAS operations (115th Congress, 2018). As of April 2020, the FAA has recognized 105 accredited post-secondary institutions in 42 states that offer UAS-related certificates or degrees (associate's or bachelor's) with a minor or concentration in UAS design, operations, and maintenance. Schools can be not-for-profit public or private, two- or four-year post-secondary accredited institutions. Candidate schools voluntarily apply to be recognized with the federal UAS-CTI distinction by offering courses that introduce students to the "use, maintenance, applications, privacy concerns, safety, and federal policies concerning UAS" (FAA, 2020). The goal of this work is to build collaborations between educational institutions, industry professionals, and governments to address the growing demand for qualified UAS professionals and sharing training best-practices and accepted standards for preparing skilled and capable UAS pilots.

Currently, there are only four higher education institutions that serve as AUVSI TOP certified training providers, all are FAA CTI-UAS members. Each institution has integrated the TOP certification process into their programs in unique ways that result in student certification in conjunction with their academic coursework. This approach is unique compared to available certifications for geospatial professionals seeking UAS training experience (e.g., land surveyor, Geographic Information System analysts, photogrammetrist, cartographers). For example, the American Society for Photogrammetry and Remote Sensing (ASPRS) requires at least three years of experience in a UAS related profession or completion of a higher education degree with relevant coursework to become a Certified Mapping Scientist, UAS (`https://www.asprs.org/`). The following four examples highlight how a professional UAS certification can be integrated into higher education institutions.

1. Embry-Riddle Aeronautical University – Worldwide was instrumental in helping to develop AUVSI TOP protocols and was the first university to become an AUVSI TOP certified provider through its coursework-based "sUAS Operations Certificate" program. By integrating the TOP certification into existing coursework, Embry-Riddle students have the option to earn all three levels of the TOP professional UAS pilot certification at a reduced cost and complete fundamental proficiency in crew resource management, effective communication, aeronautical decision-making, and airmanship principles as part of their TOP participation and concurrent course enrollment.

2. Virginia Tech University integrated the AUVSI TOP certification program into its African Drone and Data Academy (ADDA). The TOP certification is part of a UNICEF-sponsored African educational partnership with Malawi University of Science and Technology, offering opportunities for students at both institutions to train and be certified, on the design, operation, and maintenance of UAS in support of the Humanitarian Drones Testing Corridor (Mkuwu et al., 2022). Malawi students gain hands-on experience in aerial image surveys for humanitarian crises, natural disaster monitoring and response, UAS mobile Wi-Fi connectivity, and transport of emergency medical supplies, vaccines, and laboratory samples.

3. North Carolina State University (NCSU) offers TOP certifications free-of-charge to enrolled NCSU students and at reduced costs for faculty, staff, and active-duty military and military veterans. NCSU offers all

TOP certification levels through its Institute for Transportation Research and Education (ITRE) which offers a range of transportation education programs.

4. Warren County Community College is the first 2-year institution to offer all levels of AUVSI TOP certification – including instructor training. Warren is only one of six entities globally that can certify all levels of the AUVSI TOP certification, including Remote Pilot Instructor. Warren has built the Part 107 knowledge preparation, AUVSI TOP certifications, and industry-recognized software certifications in Pix4D photogrammetric and Esri ArcGIS geographic information systems software.

Integrating professional certifications, like AUVSI-TOP, into accredited higher education programs has advantages for students, institution programs, and the certifying organization. Students receive an industry-recognized mark of accomplishment during their academic coursework that validates their knowledge, skills, and commitment to a career pathway, many times at a reduced cost financially. Certifications can incentivize student persistence in a major and provide a competitive edge in future job pursuits (Stuart et al., 2014). Institutionally, certifications can lead to an improved competency-based curricular design, increased teaching quality and educator self-confidence, and ensure that faculty and staff maintain current industry standards and continued professional development (Mbise, 2021). Institutions also gain industry-recognized credibility that can complement existing accreditation and promote future enrollment and programmatic growth. Certifying organizations also benefit from their affiliation with higher education institutions, gaining credibility as a recognized training standard endorsed by institutions that already engage in a rigorous accreditation process.

There are some challenges with this approach as well. Integrating professional certifications, like AUVSI-TOP, into accredited higher education programs requires faculty and department resources to design curricula, align learning objectives and activities with certification protocols, and prepare for the audit process. For programs with well-developed UAS-based aviation programs and degree offerings, this process can be expedited more easily. Competency-based certifications demonstrating flight proficiency also require a greater commitment of resources to maintaining a UAS training fleet and secure space for acceptable training field sites, storage, and laboratory facilities. Several challenges can also emerge with the implementation of agency and academic partnerships. First, it is not clear how broadly the AUVSI TOP program will be instituted and how widely it would be accepted among new and existing commercial UAS remote pilots and prospective employers. Although ANSI and AUVSI are working collaboratively to define standards for UAS safety and professional conduct, AUVSI TOP has not completed an accreditation from the American National Standards Institute Certificate Accreditation Program (ANSI-CAP) since accepted standards are still in the drafting process. Completing this accreditation process could provide the necessary endorsement needed to require such a certification program. Currently, it is up to individuals and organizations to voluntarily pursue training certification opportunities.

The U.S. Department of Education (DoE) could partner with the globally recognized American National Standards Institute (ANSI) to establish a higher education initiative that partners ANSI-CAP, the FAA CTI-UAS intiative, and AUVSI TOP to support 2- and 4-year institutions seeking to integrate drone technologies and drone programs into their institutions. Grant funding could cover the costs associated with training and certification of faculty as TOP providers and accelerate professional certification as a standard across the industry.

Both of the professional certification solutions outlined, commercially available and higher-education integrated, could build public trust in commercial pilot operations if widely adopted. However, these approaches do not offer a solution for the remaining 448,868 recreationalist pilots that currently make up almost 60% of the U.S. drone community. Recreationalists are operating entirely on the minimal federal requirements for safety compliance by completing the online TRUST certificate and it is unclear how many recreationalists are knowledgeable and compliant with the growing number of state and local laws, and respectful of public concerns and the superadjacent airspace environment. The recreational aviation community does have well-established representation nationally through the Academy of Model Aeronautics (AMA) that could provide a pathway for additional education and outreach related to state and local regulations for recreational users. The AMA, founded in 1936 has over 200,000 active members and 2,400 clubs in the U.S. and Puerto Rico. Recently, the FAA, in partnership with the AMA, AUVSI, and Consumer Technology Association (CTA), has organized an education campaign called, the Know before you Fly campaign (`https://knowbeforeyoufly.org/`) to provide new drone users with information and guidance they need to fly safely and responsibly. Like much of the outreach material designed by the FAA, the information available on the "Know before you fly" website is largely aimed at safety and provides little information or access to resources to stay knowledgeable of state and local regulations. The program's website does provide summary information from its NTIA voluntary best practices but offers little guidance on compliance (`https://knowbeforeyoufly.org/get-started/uas-best-practices`). The AMA, AUVSI, and CTA could partner with states to host a searchable listing of the most up-to-date state laws and local regulations on the knowbeforeyoufly.org website. To the best of our knowledge there is not an accessible and up-to-date resource for UAS pilots and operators to access relevant state and local statues. Drone-laws.com does host an open-source volunteer-based posting of drone laws and regulations but the page lacks consistent formatting, is difficult to navigate, does not meet accessibility standards, and provides inconsistent resource links to validate source credibility. (`https://drone-laws.com/drone-laws-by-states/`).

## 5.5 Discussion

Advancing innovation and the beneficial uses of uncrewed aircraft while protecting privacy and promoting aviation safety will require advances in training and certification approaches that can address actual flight proficiency and professional best practices critical to drone operations.

Part 107 approved testing facilities for commercial and public safety pilots are already accessible through the FAA's Integrated Airman Certification and Rating Application (IACRA) (`https://iacra.faa.gov/`) and most are located at flight training centers with staff that are already certified flight instructors (CFI) for crewed aircraft. CFI-qualified staff could be trained to administer a physical or simulator version of a NIST/ASTM standardized drone flight proficiency examination. A simulator version of the NIST/ASTM proficiency course has recently been designed by Zephyr Simulations (`https://zephyr-sim.com/`) and could be utilized for outreach, training, and proficiency assessment to certify recreationalists, commercial pilots, and public safety pilots.

Drones operate in superadjacent airspace which raises privacy concerns and drone pilots need training opportunities and a certification process that equips them with the knowledge and skills needed to identify and mitigate risks to privacy posed by drone operations. In 2016, the FAA issued a final rule on the "Operation and Certification of Small Uncrewed Aircraft Systems" and avoided addressing privacy concerns, stating that "privacy concerns have been raised regarding the integration of drones into the NAS" but privacy issues "are beyond the scope of this rulemaking" (14 CFR 89 § 44809, 2021). A non-governmental certifying organization could provide training and certifications that assess knowledge of federal safety standards, proficiency of flight operations, and best practices for meeting state privacy regulations. There are existing federally approved NIST standards for privacy and security awareness training that could be integrated into a certification that meets federal and state standards for safety, privacy, and security. The NIST "Special Publication 800-53 (Revision 4) Appendix J — Privacy Awareness Training" specifies standards for privacy controls and contains training modules regarding privacy and security awareness training. The NIST 800-53 standards are one of the most relied-upon privacy and security standards used by federal agencies, state governments, and organizations. The standards could be used as a framework for designing training and assessment of drone pilots for certification. Additionally, the UAA's UAS Pilot Code and NTIA's Voluntary Best Practices for UAS Privacy, Transparency, and Accountability could provide themes for developing training and testing scenarios that evaluate a commercial pilots' ability to identify the possible impacts of drone operations on privacy and methods for mitigating risks to privacy.

Setting clear expectations for responsible conduct and creating clear standards are critical first steps in better defining a social contract between commercial drone technology and society. As the civil uses for UAS continue to expand in the U.S., providing a drone-specific training and certification framework that addresses airspace safety and privacy protections will be an essential part of establishing public trust and advancing the beneficial uses of the technology. A federal certification framework has been established for commercial and recreational pilots to address knowledge of safety rules and regulations. UAS professionals need a unified training and certification framework, accredited by non-governmental certifying organization, that assesses professional remote pilots' knowledge of federal airspace safety rules and regulations, actual flight maneuvering proficiency, and awareness of best practices for reducing risks to privacy. Pursuing professional certifications demonstrate a commitment to professionalism, upholding industry standards, and an openness to continued learning. The FAA has cautioned that its regulatory authority only pertains to matters of aviation safety and states are exercising their land use and policing powers to enact privacy laws. Ultimately, it is the responsibility of drone pilots to demonstrate their commitment to safe and responsible use of the technology. This means demonstrating their knowledge of safety regulations, and operating requirements while acting with the highest level of professionalism and respect for others' reasonable expectations of privacy.

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# Appendix A

# Supplemental Figures

**CNN + OBIA**

| Site | Metric | *A. fasciculatum* | *A. pumila* | *A. tomentosa* | *C. rigidus* | Standing Deadwood | Bareground | Coastal Sage Scrub | *Q. agrifolia* | OA | Kappa |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Site A | Precision | 0.83 | 0.96 | 0.78 | 0.17 | 0.82 | 0.94 | 0.82 | 0.95 | 0.87 | 0.84 |
| | Recall | 0.91 | 0.92 | 0.97 | 1.00 | 0.96 | 0.93 | 0.76 | 0.74 | | |
| | F1 | 0.87 | 0.94 | 0.86 | 0.29 | 0.88 | 0.93 | 0.79 | 0.83 | | |
| | Kappa | 0.81 | 0.94 | 0.74 | 0.17 | 0.81 | 0.94 | 0.78 | 0.94 | | |
| Site C | Precision | 0.75 | 0.94 | 0.67 | 0.13 | 0.96 | 0.98 | 0.81 | 0.99 | 0.85 | 0.82 |
| | Recall | 0.33 | 0.81 | 0.88 | 0.75 | 0.96 | 0.91 | 0.78 | 0.94 | | |
| | F1 | 0.46 | 0.87 | 0.76 | 0.22 | 0.96 | 0.94 | 0.79 | 0.96 | | |
| | Kappa | 0.75 | 0.90 | 0.63 | 0.12 | 0.96 | 0.98 | 0.78 | 0.98 | | |
| Site D | Precision | 0.88 | 0.78 | 0.87 | 0.22 | 0.92 | 0.97 | 0.56 | 1.00 | 0.83 | 0.78 |
| | Recall | 0.80 | 0.87 | 0.90 | 0.64 | 0.86 | 0.92 | 0.55 | 0.80 | | |
| | F1 | 0.84 | 0.82 | 0.88 | 0.33 | 0.89 | 0.94 | 0.56 | 0.89 | | |
| | Kappa | 0.84 | 0.74 | 0.79 | 0.21 | 0.91 | 0.97 | 0.51 | 1.00 | | |
| Training Site | Precision | 0.93 | 0.93 | 0.92 | 0.19 | 0.94 | 0.95 | 0.90 | 0.98 | 0.91 | 0.89 |
| | Recall | 0.78 | 0.93 | 0.90 | 0.92 | 0.87 | 0.98 | 0.82 | 0.96 | | |
| | F1 | 0.85 | 0.93 | 0.91 | 0.31 | 0.90 | 0.96 | 0.86 | 0.97 | | |
| | Kappa | 0.92 | 0.89 | 0.90 | 0.18 | 0.94 | 0.94 | 0.88 | 0.97 | | |

Figure A.1: Accuracy Assessment of CNN and OBIA deep-learning landscape cover classification.

RF

| | | *A. fasciculatum* | *A. pumila* | *A. tomentosa* | *C. rigidus* | Standing Deadwood | Bareground | Coastal Sage Scrub | *Q. agrifolia* | OA | Kappa |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Site A | Precision | 0.16 | 0.92 | 0.68 | 0.45 | 0.78 | 0.88 | 0.41 | 0.74 | 0.64 | 0.57 |
| | Recall | 0.76 | 0.74 | 0.83 | 0.05 | 0.79 | 0.85 | 0.43 | 0.61 | | |
| | F1 | 0.26 | 0.82 | 0.75 | 0.09 | 0.79 | 0.87 | 0.42 | 0.67 | | |
| | Kappa | 0.13 | 0.89 | 0.63 | 0.41 | 0.77 | 0.88 | 0.30 | 0.69 | | |
| Site C | Precision | 0.00 | 0.88 | 0.28 | 0.46 | 0.78 | 0.97 | 0.31 | 0.89 | 0.70 | 0.62 |
| | Recall | 0.00 | 0.72 | 0.38 | 0.37 | 0.79 | 0.96 | 0.77 | 0.80 | | |
| | F1 | - | 0.79 | 0.32 | 0.41 | 0.78 | 0.97 | 0.44 | 0.84 | | |
| | Kappa | -0.02 | 0.80 | 0.21 | 0.42 | 0.76 | 0.97 | 0.27 | 0.86 | | |
| Site D | Precision | 0.21 | 0.74 | 0.66 | 0.26 | 0.49 | 0.92 | 0.38 | 0.82 | 0.56 | 0.46 |
| | Recall | 0.46 | 0.72 | 0.77 | 0.09 | 0.83 | 0.94 | 0.34 | 0.26 | | |
| | F1 | 0.29 | 0.73 | 0.71 | 0.13 | 0.61 | 0.93 | 0.35 | 0.39 | | |
| | Kappa | 0.13 | 0.69 | 0.51 | 0.21 | 0.47 | 0.92 | 0.30 | 0.77 | | |
| Training Site | Precision | 0.49 | 0.87 | 0.72 | 0.08 | 0.90 | 0.90 | 0.64 | 0.85 | 0.77 | 0.71 |
| | Recall | 0.73 | 0.84 | 0.56 | 0.63 | 0.84 | 0.95 | 0.67 | 0.93 | | |
| | F1 | 0.59 | 0.85 | 0.63 | 0.14 | 0.87 | 0.92 | 0.65 | 0.89 | | |
| | Kappa | 0.48 | 0.81 | 0.62 | 0.07 | 0.89 | 0.90 | 0.60 | 0.81 | | |

Figure A.2: Accuracy Assessment of Random Forest landscape cover classification.

SVM

| | | A. fasciculatum | A. pumila | A. tomentosa | C. rigidus | Standing Deadwood | Bareground | Coastal Sage Scrub | Q. agrifolia | OA | Kappa |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Site A | Precision | 0.51 | 0.98 | 0.80 | 0.09 | 0.72 | 0.97 | 0.26 | 0.13 | 0.62 | 0.54 |
| | Recall | 0.72 | 0.56 | 0.60 | 0.03 | 0.77 | 0.83 | 0.95 | 0.73 | | |
| | F1 | 0.60 | 0.71 | 0.69 | 0.04 | 0.75 | 0.89 | 0.41 | 0.22 | | |
| | Kappa | 0.45 | 0.96 | 0.74 | 0.06 | 0.71 | 0.97 | 0.23 | 0.11 | | |
| Site C | Precision | 0.00 | 0.92 | 0.47 | 0.38 | 0.89 | 0.98 | 0.52 | 0.96 | 0.79 | 0.73 |
| | Recall | 0.00 | 0.77 | 0.57 | 0.65 | 0.95 | 0.94 | 0.93 | 0.8 | | |
| | F1 | - | 0.84 | 0.52 | 0.48 | 0.92 | 0.96 | 0.67 | 0.87 | | |
| | Kappa | -0.01 | 0.88 | 0.41 | 0.36 | 0.88 | 0.98 | 0.48 | 0.95 | | |
| Site D | Precision | 0.23 | 0.92 | 0.83 | 0.1 | 0.61 | 0.98 | 0.23 | 0.18 | 0.61 | 0.48 |
| | Recall | 0.76 | 0.51 | 0.60 | 0.17 | 0.77 | 0.79 | 0.91 | 0.94 | | |
| | F1 | 0.35 | 0.66 | 0.70 | 0.13 | 0.68 | 0.87 | 0.37 | 0.30 | | |
| | Kappa | 0.18 | 0.89 | 0.66 | 0.08 | 0.59 | 0.98 | 0.21 | 0.17 | | |
| Training Site | Precision | 0.24 | 0.89 | 0.75 | 0.00 | 0.82 | 0.94 | 0.68 | 0.93 | 0.79 | 0.74 |
| | Recall | 0.89 | 0.85 | 0.60 | - | 0.80 | 0.98 | 0.72 | 0.91 | | |
| | F1 | 0.38 | 0.87 | 0.67 | - | 0.81 | 0.96 | 0.70 | 0.92 | | |
| | Kappa | 0.23 | 0.85 | 0.66 | 0.00 | 0.81 | 0.94 | 0.64 | 0.91 | | |

Figure A.3: Accuracy Assessment of Support Vector Machine landscape cover classification.

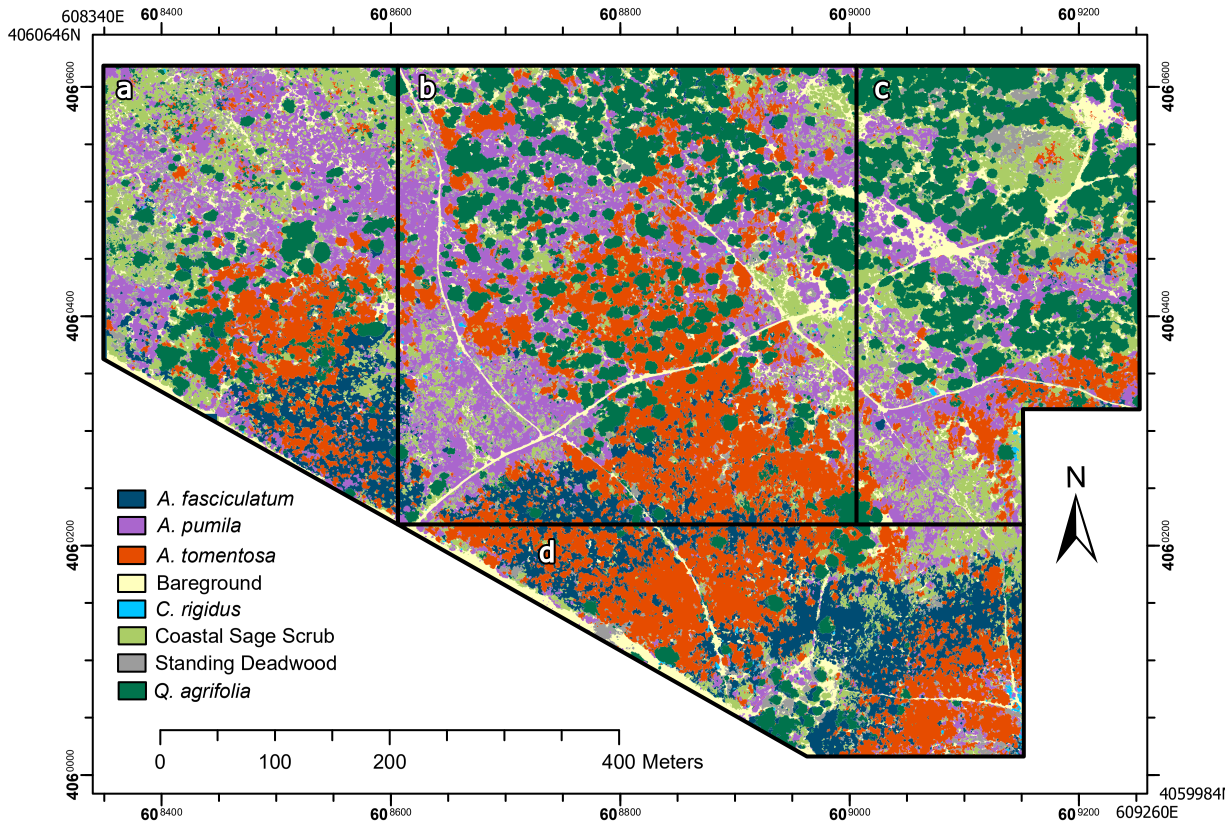


Figure A.4: CNN+OBIA land cover classification results (WGS 84 UTM Zone 10 projection). a) Application Site 1 (7.43ha), b) Training Site (16ha), c) Application Site 2 (9ha), d) Application Site 3 (8ha).

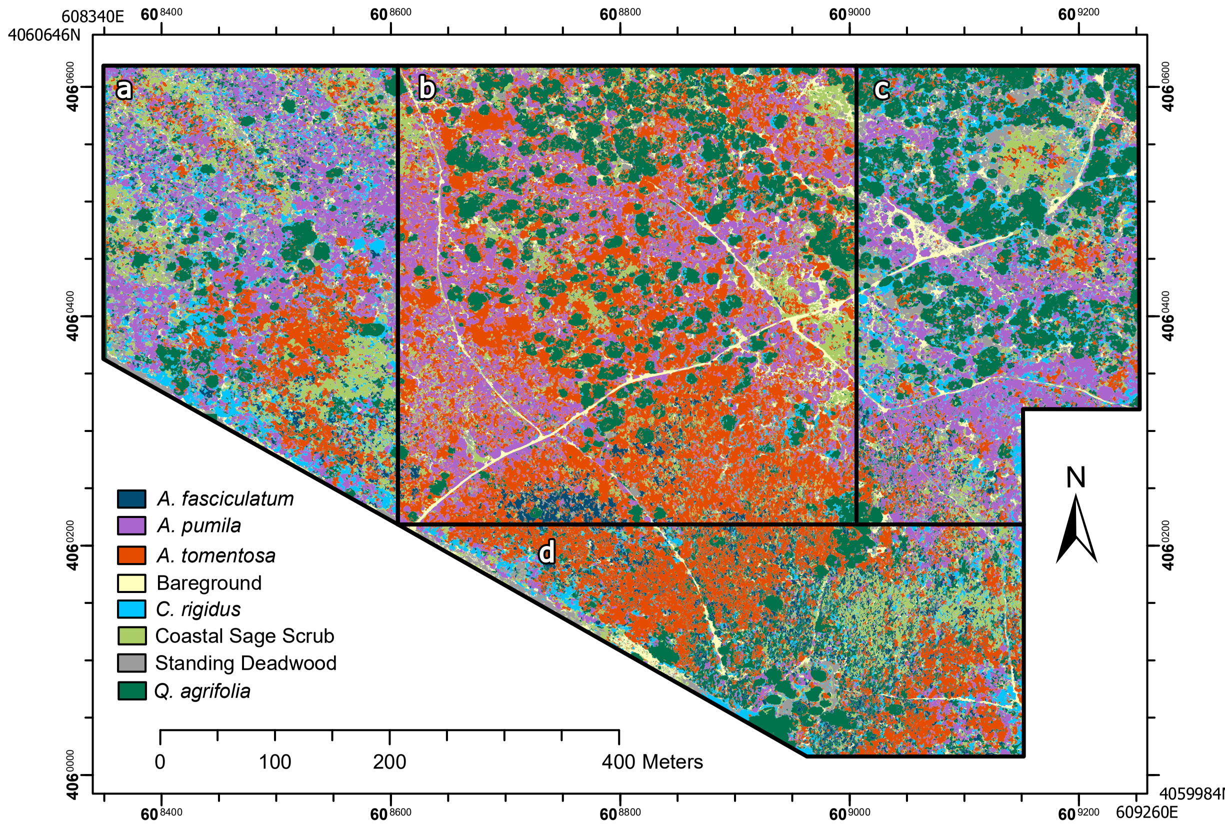


Figure A.5: Random Forest classification results (WGS 84 UTM Zone 10 projection). a) Application Site 1 (7.43ha), b) Training Site (16ha), c) Application Site 2 (9ha), d) Application Site 3 (8ha).

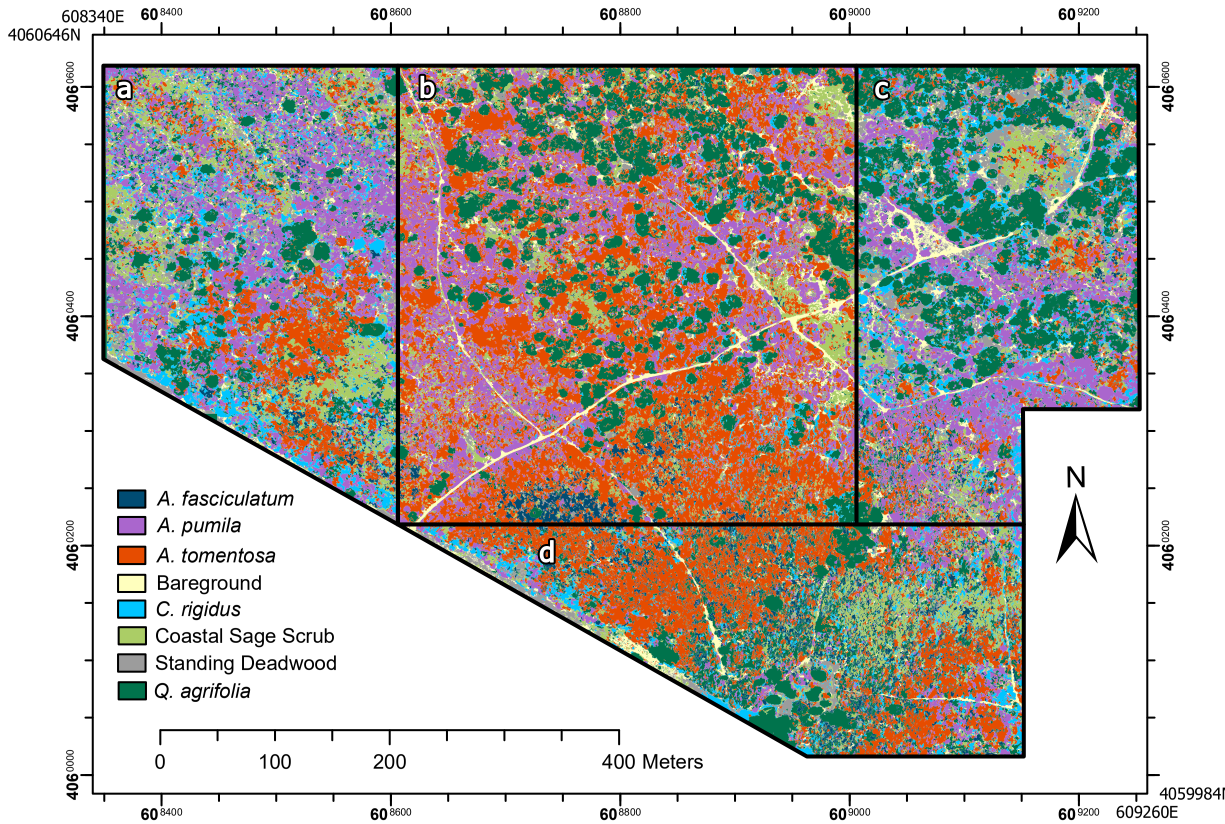


Figure A.6: classification results (WGS 84 UTM Zone 10 projection). a) Application Site 1 (7.43ha), b) Training Site (16ha), c) Application Site 2 (9ha), d) Application Site 3 (8ha).