AN EXPLORATORY ASSESSMENT OF HIGH-RESOLUTION DRONE IMAGERY AND DEEP LEARNING TO SUPPORT INVASIVE SPECIES MANAGEMENT

by

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Abstract

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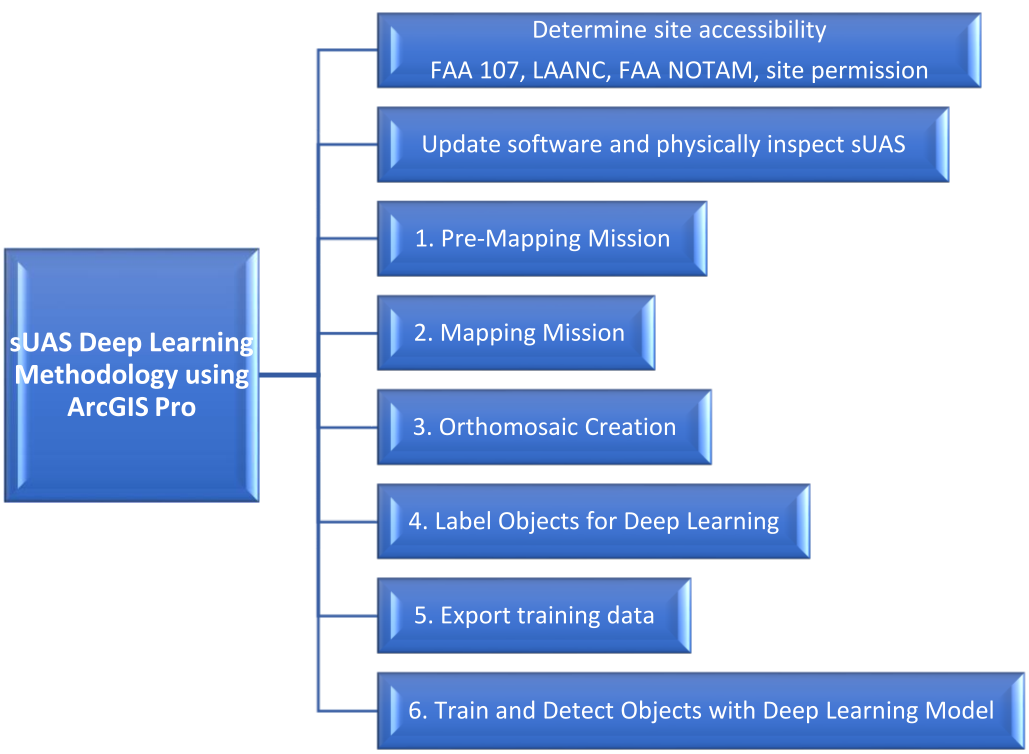
Rapid and low-cost ecological monitoring using drone-acquired imagery and videography has the potential to address contemporary environmental challenges. This study explored the application of these methods, specifically machine or deep learning, for long-term monitoring of invasive species during phase IV of ecosystem-based management (EBM). The objective was to evaluate the usefulness of drones in managing invasive species while considering various constraints faced by managers. The research focused on machine learning techniques using *Cytisus scoparius* (Scotch broom) as a case study, highlighting the challenges, limitations, and workflows involved in creating a database using aerial-derived imagery captured during winter with a low solar zenith angle. Additionally, this study investigated the integration of low-cost RGB aircraft and non-precision GPS as alternatives to reduce long-term costs for resource-limited organizations. Although survey-grade aircraft and equipment currently present significant barriers to entry due to high costs, this research demonstrates that inexpensive RGB drone imagery can effectively develop high-resolution orthomosaics within these constraints and moderately support a deep learning model with approximately 50% precision scores. This study contributes to future research by showcasing the methodology used to acquire, integrate, and utilize drone imagery within the ArcGIS software suite to inform EBM policy and management decisions alongside real world challenges faced by ecosystem managers and caretakers.



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1. Introduction

Mismanaged ecosystems are vulnerable to disease and invasive species. Addressing these risks becomes increasingly difficult due to the combined pressures of climate change and anthropogenic disturbances faced by ecosystem managers globally (IPCC, 2023; NOAA, 2022; UNEP, 2021). These challenges are often strategically addressed using ecosystem-based management (EBM), an integrated and systems-thinking approach that considers both human and ecological factors (Asenova, 2018; Colomina & Molina, 2014; O'Higgins et al., 2020). Furthermore, the relentless loss of forest canopy, resulting in the depletion of approximately 33% of the Earth's historical global coverage, serves as a stark reminder of the urgency to address these concerns (NOAA, 2022; Ritchie, 2021). Implementing global change to address these issues may appear daunting and cause apprehension; however, employing meaningful solutions at a local or regional level may offer a variety of benefits as well as tradeoffs such as increased cost or a lack of supporting infrastructure.

Local, or regional management allows for a more focused understanding of the specific invasive species and their impacts on the local ecosystem (O'Higgins et al., 2020). This knowledge is essential for developing targeted strategies that address the unique challenges posed by invasive species within the context of the area. Additionally, such management facilitates closer collaboration and engagement with relevant stakeholders, including local communities, landowners, and resource managers (O'Higgins et al., 2020). This involvement ensures that management decisions and actions are informed by local knowledge and priorities, leading to increased support and compliance. Furthermore, by operating at a smaller scale, local or regional management enables more efficient and effective monitoring, early detection, and rapid response to invasive species outbreaks. This proactive approach can help contain and prevent the spread of invasives, minimizing their ecological and economic impacts (O'Higgins et al., 2020). Ultimately, incorporating invasive species management at a local or regional level of EBM promotes adaptive, context-specific approaches that are better suited to address the complexities and challenges associated with invasive species.

Local forests provide essential ecosystem services such as shelter, erosion control, carbon sequestration, noise reduction, groundwater filtering and retention, recreation, and many others. Invasive species pose a threat to native flora, fauna, and regional economies but also hinder the overall effectiveness of ecosystem restoration initiatives. An example of a local vulnerability exists at post clearcut logging sites in the Pacific Northwest, specifically with the example invasive species used in this study, *Cytisus scoparius* (Scotch broom).

Scotch broom rapidly colonizes newly disturbed landscapes and often lacks natural enemies in its non-native environment. Scotch broom is particularly well-suited to high sunlight and low nitrogen environments, thanks to its adaptation as a nitrogen-fixing legume in dry Mediterranean climates (Hill et al., 2016). Despite its vibrant yellow blooms, Scotch broom degrades natural ecosystems and acts as ladder fuel in forest fires, while also outcompeting and displacing native flora, particularly along roadsides, pastures, and deforested areas (Underwood et al., 2019; Hill et al., 2016). The subsequent loss of reliant consumer species further exacerbates the decline in plant biodiversity. Additionally, the Scotch broom plant secretes flammable oil that protects its leaves and stems, making it an intriguing candidate for management, particularly monitoring in Western Washington. These distinct characteristics of the Scotch broom make its removal a potential concern in the coming years which is where EBM intersects this invasive species and its management.

EBM, rooted in the theory of adaptive management's six steps (assess, design, implement, monitor, evaluate, and modify), provides a dynamic and structured approach to ecosystem management (O'Higgins et al., 2020). EBM, specifically in phase IV, which encompasses implementation, monitoring, and evaluation, tends to be both time-consuming and expensive (O'Higgins et al., 2020; Wasson et al., 2015). The constraints of time and associated costs often hinder managers' ability to effectively oversee a site, especially in approaches that require frequent monitoring, feedback, and sufficient funding and support.

Traditional image and survey acquisition methods, such as geospatially precise satellite observations, aerial surveys, and manual ground surveys, incur significant costs over time. In addressing the limitations of EBM phase IV, small-unmanned aerial vehicles (sUAVs), commonly known as drones, have emerged as a promising technology. Recent advancements in the sUAV, or small-unmanned aircraft systems (sUAS)s and geographical information system (GIS) industries have brought potential benefits to phase IV of EBM, particularly through the integration of Python-based deep learning models originally developed for the agriculture industry, alongside robust geospatial tools for invasive management. This presents an opportunity to explore the replicability, cost-effectiveness, and time efficiency of incorporating these technologies during the winter flying offseason. SUAS provide near real-time video and photo options for a site, can be deployed readily and rapidly, and with some adjustments and additional steps can create functional maps with minimal distortions and projection errors with resolutions as high as 1-2 cm per pixel.

Implementing high resolution sUAS-derived imagery and a deep-learning model show great potential to benefit EBM at small to medium sized locations using inexpensive equipment and established workflows. While this research's focus was phase IV, the sUAS-derived deep learning model may contextually benefit the entire invasive management process within EBM theory. To that end, this research aims to answer the following:

Can sUAS-derived imagery, workflows, and methodology-supported deep learning be integrated into EBM phase IV in a replicable, cost-effective, and time-efficient way during the winter flying offseason?

Overview of Methodology

The innate ability for EBM practitioners to revert to system linkage points in any of the four EBM phases also supports the Environmental Systems Research Institute's (ESRI) deep learning packages library used in this research. ESRI Indonesia developed the deep-learning package in their proprietary ArcGIS Pro flagship program as an agricultural monitoring tool. The methodology used in this research maintains a core foundation of safety and redundancies to limit and mitigate any potential impacts. To a large degree, this research incorporates the sum of human knowledge pertaining to this topic within the constraints of my own time and research queries. The methods are broken down into six major steps:

1. Pre-mapping mission: This step involves determining flight parameters, safety inspections, ground control if relevant, and other permissions for the deep learning mission flights.
2. Mapping mission: This step validates the VLOS, GPS and includes aerial data collection and storage.
3. Orthomosaic creation: Using the aerial imagery acquired, this step created a composite or stitched image to remove and mitigate distortions and errors from the image collection that is used as the backbone of the deep learning model.
4. Label objects for deep learning: This step involved the manual labeling and identification of appropriate samples for the spatial database.

5. Export training data: This involved the use of metadata and storage formats so that a relevant deep learning model may be selected.
6. Train and detect objects: These were the final training step for this research, a culmination of the other steps plus constraints. This step shows the effectiveness (precision, recall, and f1 score) of the model and limitations for future off season sUAS flights.

Constraints

The primary objective of this research endeavor was to establish a foundation for integrating a Python-based deep learning model into future EBM projects using a small dataset of Scotch broom. Several constraints were applied, reflecting the challenges of EBM across diverse environments, monitoring expenses, and seasonal challenges.

One such constraint pertained to weather conditions and the use of drones. It should come as no surprise that our region experiences frequent rainfall, rendering most contemporary sUAS unsuitable for operation in such conditions. The high levels of humidity and light precipitation prevalent here can ground drone pilots for extended periods, and the potential risk of drone accidents poses substantial financial liabilities, including damage to the environment and third parties.

Furthermore, site accessibility on foot posed additional dangers, particularly in areas prone to landslides and avalanches. Given the abundance of mountainous terrain in our region, I simulated restricted site access during the development of the test database. Additionally, the proximity of the database location to my residence allowed for convenient mapping missions within a 15-minute radius, contingent upon favorable weather conditions.

Another unintentional constraint arose from the recommended sampling size of 600 by ESRI for machine learning purposes (Abdilah, 2021). This recommendation served as a useful baseline for model testing and proof of concept. It provided valuable insights for further and future analysis, which will be presented later in the research.

Considering the Pacific Northwest's geographical location around the 47th parallel, the physics of remote sensing dictates the need for moderate sunlight to capture accurate imagery. For instance, a cloudy day in August around noon would yield optimal images due to the near-overhead positioning of the sun, resulting in minimal shadows and evenly scattered light rays. Conversely, capturing images under similar conditions in February would prove suboptimal, characterized by distortions, artifacts, and poorly generated tie points, as the mapping software relies on more shadows for referencing and pairing.

Lastly, financial considerations played a pivotal role throughout this research. The aim was to accomplish all research aspects with minimal fiscal inputs, aligning with the constraint of simulating restricted accessibility. Consequently, the use of high-precision GPS equipment, which typically incurs substantial costs, was circumvented, and less accurate alternatives were employed, albeit with inherent challenges. Additionally, adhering to ESRI's deep learning methodology contributed to mitigating financial impacts, as an established framework for conducting this type of work was already in place. It is well known that budgetary constraints often impede the implementation of ideas within environmental management, including environmental remediation and the exploration of alternative plans. Moreover, limited funding invariably translates to a scarcity of computational resources, further underscoring the significance of financial considerations in this research endeavor.

In addition to the constraints above, this research aims to showcase these workflows for EBM so that future land managers can implement a cost-effective drone program that suits their site-specific requirements. Using ESRI workflows and pre-programmed autonomous missions ensures that the products are precise, viable, and easily replicable to the standards utilized during data acquisition and processing. A benefit of including ESRI workflows in this research was that their workflows are updated with every patch and updated release of ArcGIS Pro software and supported by their customer service team. Moreover, saving and preparing mission plans gives an equal or similar ground sampling distance (GSD) amongst all past, current, and future missions. A GSD is a real-world measurement represented by averaging the distance between the center of adjacent pixels on the corrected image. sUAS allows for greater resolution which may allow for greater recognition of relevant species, such as the Scotch broom example.

Significance

This work can potentially become a rigorous addition to monitoring ecosystem management. In addition, we can survey and monitor the landscape, plant growth during the restoration stages, invasive species, and property boundaries with a circular error as low as one or two feet when using precision GPS. Both sUAS and precision GPS devices have assisted in documenting the aftermath of logging and forest restoration activities amongst many other industrial uses. One example motivating my work was a city-owned land tract adjacent to the Cooper Crest restoration site that was illegally logged. This activity was found using precision GPS and several sUAS flights during August 2022.

While the use of precision GPS is clearly demonstrated time and time again, this research sought to determine if cutting this cost out of the equation is possible or relevant in many situations. Being able to identify thick stands of invasive species may not require centimeter levels of accuracy and would certainly reduce the need for large restoration parties consisting of Conservation Corps members. This combination of technology effectively demonstrated several potential use cases as they ultimately initiated litigation against the logging company when a professional surveyor corroborated Mike Ruth's and my findings. Additionally, sUAS are rapidly deployable, operate at a fraction of the cost of piloted aerial photography, and can provide unmatched detail of small to large work sites.

This research adopted the constraints noted above and may be significant in that it shows a glimpse of the minimum requirements for incorporating sUAS into EBM and other environmental management practices. Frequently, the agricultural industry uses expensive sUAS with multispectral capabilities and permanent ground control points, which is not always possible with EBM activities. I decided to attempt an RGB-supported analysis that would add value to the literature, whether it was effective or not. With that in mind, this research incorporated a readily available and inexpensive sUAS platform with an RGB remote sensor. Secondly, the database creation simulated being unable to step on a site. This means limited GPS corrections without ground control points, real-time kinematic, or post-processing kinematic services.

This research seeks to incorporate sUAS into EBM using high resolution imagery as the backbone for a spatial deep learning model using ESRI GIS software. This objective coincides well with for the need for reproducible and replicable sUAS GIS products that could be critical for other community members, non-governmental organizations, land managers, or anyone needing low-cost-high, efficiency mapping and monitoring techniques (Howe & Tullis, 2022). In addition, having a conceptual model for dynamically sized worksites and computer analysis workflows will aid in increasing precision and efficiency besides minimizing costs (Lee et al., 2016).

Roadmap

To address the challenges of invasive species management and leverage the potential of innovative methods, this section outlines this research's sUAS and AI-powered approach for implementing EBM at the *Cytisus scoparius* (Scotch broom) site. A description of the sites used within this research is next, followed by a literature review. The literature review grounds this research by explaining the remote sensing and AI models incorporated within this research as structured around the four key phases of EBM. These phases are societal goals, knowledge base and risk assessment, EBM plan, and implementing, monitoring, and evaluating. The use of small Unmanned Aerial Systems (sUAS) and a Python-based deep-learning model are integral components of this workflow, enabling remote sensing and data analysis for informed decision-making.

The methods section provides a detailed account of my data collection, including aerial imagery acquisition approaches, mission design, and the incorporation of GPS and Ground Control Points (GCPs) when relevant. Furthermore, it outlines the necessary steps for data preparation and storage, orthomosaic workflows in ArcGIS Pro, and the development and initial evaluation of the deep-learning model. The results section presents the intermediate products, such as the orthomosaic and deep learning model, while discussing their accuracy and implications. The discussion highlights the strengths, limitations, and challenges associated with using sUAS imagery, comparing the study with other approaches, addressing cost considerations, and exploring future directions. By following this roadmap, stakeholders can enhance invasive species management strategies, improve monitoring and evaluation techniques, and pave the way for further advancements in the field.

2. Site Descriptions

Cooper Crest Restoration and Inspiration Site

One example of a clearcut site under the care of EBM is the Cooper Crest restoration site on the northwest corner of 20th Avenue and Cooper Point Road in Olympia, WA. During the summer of 2022, Silvimantle LLC sought to mitigate financial losses and relieve investor pressure at these properties in West Olympia by logging the location and selling the remnants to anyone willing to purchase the land. With looming development costs in the multi-millions of dollars, investors wanted to pull out entirely with the most negligible possible financial losses. The city of Olympia does not have a strict anti-logging policy. However, Silvimantle LLC exploited the existing laws by combining the two smaller parcels into an approximately 23-acre operation (Thurston County, 2022). The new acreage, more significant than twenty acres, bypassed existing city ordinances and placed the proposed logging operation under the jurisdiction of the DNR per the Forest Practices Act (W.A. Legislature, 2001). The DNR frames most Forest Practice Permits as a duty that supports the school systems in Washington (Hamilton & Stusser, 2022). Shortly after the logging operation finished, the Olympia Coalition for Ecosystem Preservation (OlyEcosystems) purchased the damaged land for reforestation at a steeply discounted price (Hamilton & Stusser, 2022).

The Cooper Crest site was a seasonal contributor to the headwaters of the Green Cove Creek watershed in WRIA 13, which supports six salmonid species and is one of the highest points in Olympia (Capitol Land Trust, 2022; Thurston County, 2022). The site contains several steep slopes that drain directly into the wetlands north of the site and the lowlands, including Green Cove Creek to the west and south. The potentially damaging high-velocity and turbid runoff from these newly exposed 20+ degree hillsides create risks of water quality reduction, landslides, and localized flooding. Therefore, the standing priorities based on this site are safety, erosion control, documenting the after-effects of clearcutting, and establishing a baseline for the long-term community-involved EBM. Additionally, because the site lies within the Olympia city limits, the 60+ slash piles left from the logging were not allowed to be burned (Olympic Region Clean Air Agency [ORCAA], 2022). With that understanding, the house-sized slash piles were mulched using a tub grinder and forestry mulcher during the late summer and fall of 2022. This mulch has greatly assisted local EBM in achieving safety and erosion control priorities on this site both now and likely for years.

Upon early investigation, the site was in poor condition. The loggers decimated nearly all of the medium-sized trees and destroyed the topsoil. Additionally, several of the big leaf maples the Forest Practice permit spared toppled over in the first few winter storms of 2022, further adding to on-site safety risks. In addition, many invasive plant species on and near the site add to the problem. For example, removing nearly the entire canopy allowed Himalayan blackberry, Scotch broom, and Japanese knotweed to propagate at much greater speeds.

Initially, this project sought to incorporate the Cooper Crest site as the primary study location to monitor and autonomously study new tree plantings and the spread of invasives. However, the low presence, yet notable effects of various invasive species inspired this project to transition away from temporal studies involving reforestation to invasive monitoring and deep learning with sUAS-acquired imagery. This inspiration came from watching the Washington Conservation Corps and many volunteers work on the site, particularly the need for invasive removal. Ultimately, Scotch broom around this site and the increasing frequency I noticed on my way to and from the site led me to wonder how we can track or monitor this species during the sUAS off season.

Cytisus scoparius (Scotch broom) Site

Most of the Scotch broom was removed from the Cooper Crest site during the beginning to middle of this research. With that information in hand, it was necessary to establish a second location for database development near my home for the main body of the study. To give some perspective, the recommendations for deep learning model samples are 600 (Abdilah, 2021). This number may vary based on a model's use and degrees of freedom, however, 600 remains the recommendation from ESRI.

The number of invasives on the Cooper Crest site was further limited after the community volunteer parties and before the imagery was acquired over the winter of 2022-2023. Given the seasonal weather and nature of sUAS flights, this secondary (now primary) site location was necessary as atmospheric moisture and weather in nearly any capacity are disastrous to planning and implementing sUAS operations.

The Scotch broom site is a prime example of an unmanaged post-clearcut forest. It is close to my home in Yelm and has a safe public area for takeoff on Bald Hill Road. There is safe access to the site through the air as well as an unobstructed visual line of sight (VLOS) of nearly 90 acres. Having an unobstructed VLOS to the sUAS is a legal requirement unless granted a waiver, which is rare (FAA §107, 2012). The intent of simulating no ground site access as a constraint, among several others, is to show the versatility of sUAS. Specifically in mapping a location inaccessible on foot but still abiding by FAA regulations during the experiments by being within the VLOS. The imagery acquired at this location had thousands of samples of Scotch broom for deep learning model classifying, training, and detection and represented some of the worst density I have personally seen while also fitting the legal and study requirements.

The used portion of this site that met the legal and study requirements totaled around 20 acres of which approximately four were deemed the most sufficient. Images gathered at this location were typically around 309 flying at less than 100 feet above ground level (AGL) on many occasions. This site is heavily infested with Scotch broom and reed canary grass to the east. Additionally, the endemic trees and flora at this location were primarily deciduous which helped by limiting the number of green spectra and comparable plants in the mapping software, which subsequently made species identification significantly easier.

3. Literature Review

This literature review examines the escalating challenges posed by climate change and human-induced disturbances, emphasizing the significance of Ecosystem-Based Management (EBM) in addressing these issues. These challenges permeate various ecosystems and are exemplified by the alarming fact that the atmosphere currently bears a staggering 50% increase in CO2 levels compared to the preindustrial era (Monroe, 2022). Furthermore, it explores the potential of cutting-edge techniques, including drone-based imagery and deep learning, to enhance Phase IV of EBM. The chapter commences with a historical overview of EBM and its theoretical foundation in adaptive management. Building upon these foundational aspects, the review delves into an in-depth description of the various phases of EBM, employing the case study of Cooper Crest to exemplify its application. The research also investigates the problem of invasive species and anthropogenic impacts in this context. Additionally, it illuminates the emerging role of small Unmanned Aerial Systems (sUAS) technology as a standard tool for EBM practitioners, supported by explanations of remote sensing theory and diverse image acquisition methods. Concluding the literature review, the study briefly explores the potential of deep learning techniques and offers a synthesis of the findings using EBM as the basis of this invasive species management study.

A Concise History of EBM

Historical ecosystem and natural resource management primarily consisted of singular disciplinary approaches with visibly distinguished winners and losers (Delacamara et al., 2020; O'Higgins et al., 2020). A lack of multidisciplinary expert engagement and an often-narrow focus left most projects with partial or complete failure over the long term as they could not see the large-scale impacts to an ecosystem (Curtice et al., 2012). This lack of a multidisciplinary approach and, ultimately, additional failures regarding the northern spotted owl and Endangered Species Act (1973) helped lead to the mass adoption of EBM starting in the 1990s.

Historically, EBM may have roots with scientists and researchers such as Aldo Leopold; however, contemporary EBM in North America has deep roots with the Great Lakes Water Quality Agreement (1978) between the USA and Canada. The agreement discusses that ecosystem boundaries do not end at a park or border's edge which contextually agrees with the later notion and famous quote that “no park is an island” (Noss, 1987). Instead, they continue outward a great deal and often cross international borders (US EPA, 2015). This agreement was built upon the Boundary Waters Treaty of 1909 and helped to show further growth and collaboration between neighboring countries that support shared ecosystems and the services they provide. The success of this agreement and resulting management paradigms subsequently supported NOAAs adoption of EBM at the behest of President Clinton in the early 1990s.

Also in the 1970s, EBM was further supported by an interagency grizzly bear study team (IGBST) that found Yellowstone Park's boundary could not maintain a viable population as the megafauna did not care for human borders and required additional ecosystem access. Initially, this research was meant to investigate the closure of open pit garbage dumps and how they impacted the Greater Yellowstone Ecosystem (GYE). However, this government monitoring and research program highlighted the needs for interdisciplinary and complete ecosystem research. This approach contrasted significantly from the historical approach of using human created boundaries and borders as they found the park could not support the density of bears that it was previously thought (USGS, 2023). Ultimately, the catalyst for major EBM adoption is often considered the northern spotted owl, and forestry-related conflict that arose after the bird of prey was listed as a threatened species.

The northern spotted owl is a species of bird native to the Pacific Northwest region of the United States. In the late 20th century, its population declined significantly due to old growth forest habitat loss and fragmentation caused by logging, and exacerbated by agriculture, and other human activities. In 1990, the U.S. government listed the northern spotted owl as a threatened species under the Endangered Species Act (ESA) (1973). Following the listing, several events followed that involved implementing habitat conservation plans, timber harvest restrictions, monitoring, studies, recovery plans, litigation, and of course on-going conservation efforts shaped by these outcomes from nearly three decades ago. These subsequent actions taken were aimed at conserving resources to support the owl species and involved significant collaboration between federal agencies, stakeholders, and scientific experts in true EBM fashion (O'Higgins et al., 2020). Furthermore, these actions and events led to EBM strategies in the Pacific Northwest and helped ease subsequent adoptions from institutions and governments starting in the early 1990s.

The embracing of EBM principles and theory began with NOAA and the USFWS transitioning first in the early 1990s for marine ecosystem and fisheries management and by principally supporting conservation and policies (NOAA Fisheries, 2022). Similar acceptance was quickly followed by the US EPA and BLM (Lackey, 1998). The adoption of EBM in the USA reflects the broader global transition that was also occurring. Similar failures also caused the United Nations Environment Programme (UNEP) to adopt the ecosystem approach to management in 1995 and formally recognize the approach as EBM in 2005 which has shifted yet again to what is now called ecosystem-based adaptation (O’Hagan et al., 2020). Rather than focus on constricted political boundaries or a particular species, EBM incorporates various stakeholders, multidisciplinary experts, and the complex interactions within social-ecological ecosystems to view the problem as a part of the more extensive system (O'Higgins et al., 2020; Wasson et al., 2015).

EBM is powerful and effective in addressing complex ecosystem problems but can also be expensive, laborious, and challenging. Wasson et al. (2015) explain that EBM is effective because it encompasses many perspectives and inspires community collaboration through a common goal (pp. 63, 65-66). However, these same strengths can also hinder when funding or time are constrained, often in practical applications such as reforestation and ecosystem management or restoration.

Adaptive Management Theory

Understanding EBM further starts with briefly understanding its core theory, adaptive management. Adaptive management is a system thinking, cyclical, structured, and intentional decision-making approach. Adaptive management uses this deliberate approach to emphasize accountability and facilitate problem-solving between the community, land managers, and scientists (Kingsford et al., 2017). A typical adaptive management plan starts with establishing diverse societal or organizational goals. Goals are set in steps one and two by assessing, identifying, and determining a multi-perspective or inclusive-based management plan (Land Trust Alliance, 2021). After establishing a goal-oriented management plan, phase three sets it into motion. Phases four through six are nearly identical to EBM by monitoring, evaluating, and modifying the plan as needed.

The real-time integration of adaptive management allows for accountability by adjusting, reassessing, and modifying the plan, sometimes right back to the drawing board. Accomplishing on-the-fly modifications to a site-specific plan eliminates rigidity in historical land management. The flexibility of adaptive management in a changing world is fundamental for allowing EBM to address complex and unknown future barriers.

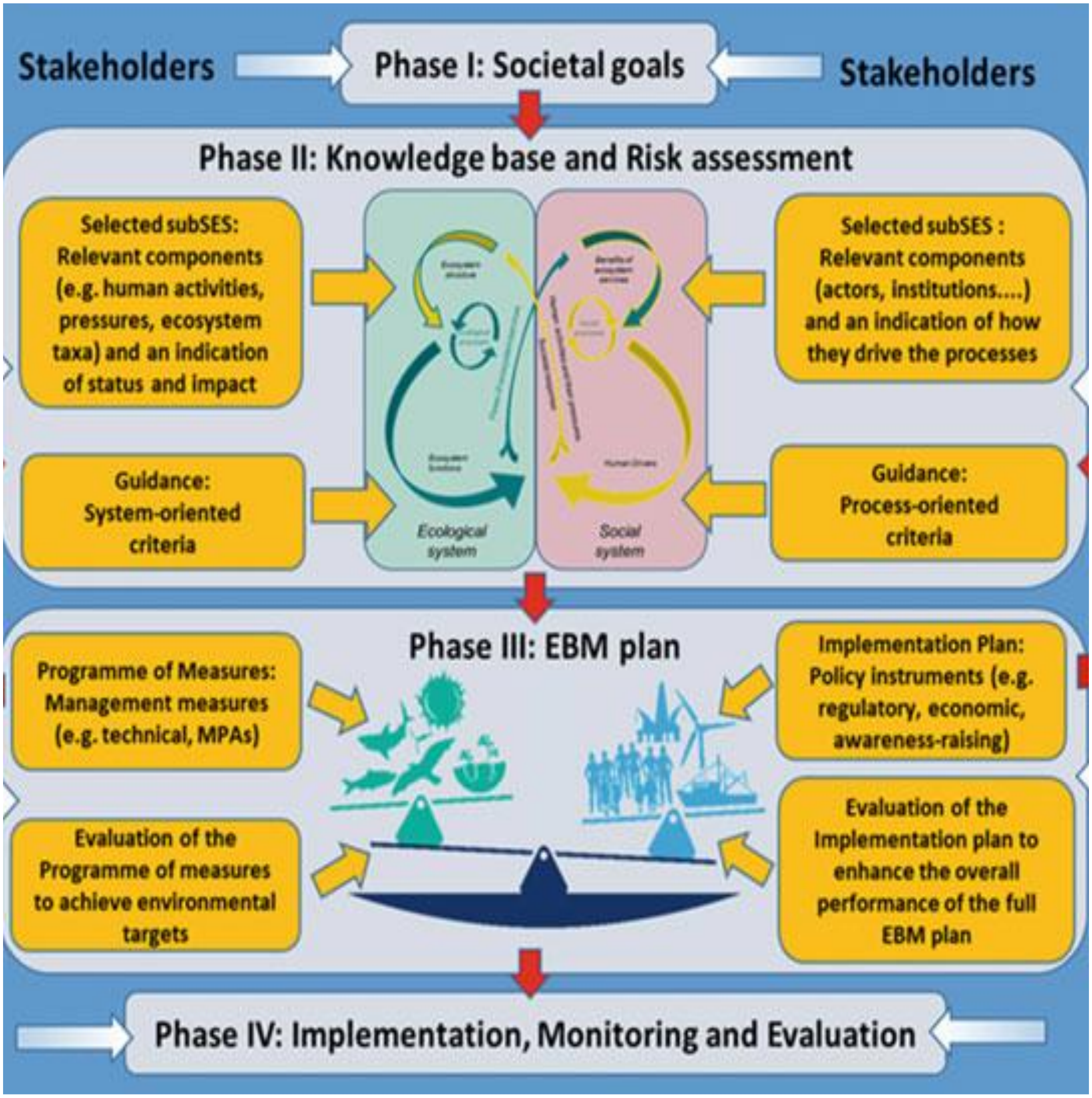
Unpacking this jargon shows that adaptive management theory is an approach that emphasizes learning and flexibility in the management of natural resources. It involves a structured decision-making process that integrates scientific research, monitoring, and feedback loops to adapt management strategies over time (Holling, 1978; Walters, 1986).

Additionally, adaptive management recognizes the complexity and uncertainty inherent in ecological systems, and it seeks to reduce uncertainties by actively testing hypotheses and learning from the outcomes of management actions. This iterative process allows for adjustments and refinements to be made based on new information and changing conditions (Allen, Fontaine, Pope, & Garmestani, 2011). Adaptive management can play a crucial role in supporting sUAS research pertaining to invasive species. By its nature, invasive species management requires continuous monitoring, assessment, and adaptive decision-making to effectively respond to changing conditions and achieve desired outcomes. sUAS technology offers a valuable tool for collecting high-resolution spatial data, such as aerial imagery and remote sensing data, which can aid in detecting, mapping, and monitoring invasive species infestations. Adaptive management frameworks can guide the integration of sUAS research into invasive species management by enabling the iterative cycle of planning, implementing, evaluating, and adjusting management strategies based on real-time data and insights. This approach allows for the refinement and optimization of control measures, spatial targeting, and resource allocation over time, ultimately enhancing the effectiveness and efficiency of invasive species management efforts.

EBM Phases and Application

Figure 1

Conceptual Model of EBM



Note. A conceptual model of EBM shows the linkages between phases and the natural progression of this theory (Piet et al., 2020). The interconnected steps allow on-the-fly experimentation and dynamic adjustment throughout the management process. In addition, the interaction of social and ecological systems helps guide the EBM plan based on site-specific and community requirements.

Phase I: Societal Goals

Similarly, to adaptive management, EBM's first phase involves setting societal goals. Typically, this phase would be regarding the sustainable maintenance of a site; however, it is not limited to maintenance (O'Higgins et al., 2020). For example, against the community's wishes, Silvimantle LLC logged several parcels at Cooper Crest in July 2022 for an investment return.

Washington manages all logging on private property under the Forest Practices Act. For the few cities that do not explicitly ban logging within the city limits, getting permission to log is often a simple process taking just a few days. The paperwork goes directly to the state office instead of the local community managing logging operations. Also of note is that as of this writing, the WADNR uses lumber money to pay for schools and other projects. They have operated under the modus operandi that logging will help fund and fight future climate changes; therefore, it is the department's responsibility to limit economic impacts.

Anthropogenic disturbances such as this are commonplace. However, the response to such a catastrophe is far from homogeneous. For example, Olympia, the capital city of the Evergreen State, failed to implement meaningful policy and did not address the necessary tradeoffs for this limited watershed. However, where Olympia failed in policy implementation, the Olympia Coalition for Ecosystem Preservation (OCEP) stepped in to manage the site using the core fundamentals of EBM.

Implementing the first phase of EBM shapes society's goals and analyzes tradeoffs associated with subsequent decisions (See Figure 1, above) (O'Higgins et al., 2020; Piet et al., 2020). Rather than allow the Forest Practices Permit to sit stagnant for ten years and become another development, OCEP and local community members sought support and determined a management plan to reforest the site. However, like many management plans, this site constituted a dynamic and challenging location, with time constraints being a significant factor.

Phase II: Knowledge Base and Risk Assessment

Phase II consists of risk assessments addressing dynamic issues and site challenges that affect the goals for a site-specific plan (Olsen et al., 2006; Piet et al., 2020). EBM is a dynamic process; therefore, setting goals are often site-specific and dependent on the results of regional risk analyses. For example, erosion, geographic makeup, and other ecosystem services likely require prioritization following a large fire or deforestation event.

The authors of a post-wildfire study discussed the need for a long-term remediation plan to maintain soil structure and one to regrow plants to restore biodiversity (Martinez et al., 2021). Similarly, the Cooper Crest site faces simultaneous challenges brought upon by the alder wood sandy loam wetland soils and the steep grades on the property (Thurston County, 2022). While tree planting was a chief worry, it was not the most immediate concern. The most immediate problem was losing an ephemeral creek and forest ecosystem services (Jones et al., 2022). The loss of so many trees threaten the wetland to the north of the property with increased runoff velocity, sedimentation, carbon loss, and turbidity (Covey et al., 2021; Jones et al., 2022). Water quality issues in The Green Cove Creek watershed may also impact chinook, chum, coho, bull trout, steelhead, and cutthroat salmonid species (Capitol Land Trust, 2022; Thurston County, 2022).

As one can see, developing even a partial management plan is a complex task, especially when considering every variable linked to a site and applicable policies to meet the community's needs. There are many criteria to address, such as biodiversity, ecosystem connections, managing uncertainty, and accumulating impacts from a dynamic ecosystem issue (Piet et al., 2020). OCEP determined that erosion control needed addressing first. This was primarily because of the site grades and inevitable rain coming to Olympia. Protecting the wetlands and site safety from these issues came in the form of the leftover slash piles, which are stacks of unmarketable trees and branches from the clear-cut logging operation, and a prime example of EBM phase III (Gromicko, 2022).

Phase III: EBM Plan

After assessing risks and determining leverage points, the planning phase incorporates the societal goals and priorities phases I and II developed. Most management planning goals in EBM focus on ecological outcomes as they extensively benefit ecosystems and reliant communities (Piet et al., 2020; Wasson et al., 2015). Determining the plan's viability to achieve the needs of the previous steps is essential in taking physical action.

Another example from Cooper Crest pertains to slash pile management, which comes in three potential forms: burning, mulching, and natural degradation (Beck & Dobson, 2022; INACHI, 2022). While using controlled burns and fire is an essential and cost-effective tool for most of human history, fire is not always the right choice. In this case, Thurston County has a burn ban during the dry season, and Olympia also has a permanent burn ban within growth management areas in the city limits (ORCAA, 2022). Given the time and money constraints around the project, leaving the slash piles to degrade naturally over many years did not seem viable. Rather than allow a slow degradation, OCEP determined that mulching the slash would be the best option (See Figure 2 below). Solidifying this part of the plan allowed OCEP to move out of the planning phase of EBM and into phase IV.

Figure 2

Cooper Crest Nadir Mulching Orthorectified Image

Note. This image shows one of the enormous slash piles after being mulched and while being spread to mitigate runoff. Additionally, the right side of this image has a grade (strong slope) of approximately 20-25% that ends when it hits Cooper Point Road right of way.

Phase IV: Implement, Monitor, and Evaluate

Phase IV is where the tires meet the pavement regarding EBM. This phase requires stakeholders and managers to work with one another through implementing, monitoring, and evaluating the chosen plan on the fly (Delacamara et al., 2020; Piet et al., 2020; Wasson et al., 2015). Incorporating the local community and schools, including colleges, supports EBM by creating robust stakeholder commitment and ample opportunity to interact with the restoration process (Wasson et al., 2015). Continuing with the mulching example shows an effective utilization of local resources and linkage points for sUAS incorporation.

Mulching the slash piles impacted the project by mitigating erosion, providing ground cover, maintaining some hydrologic function, and as a nutrient base for the long-term tree planting and monitoring that is part of the management plan. Mulching the 60-plush slash piles cost OCEP approximately $80,000; however, mulching on-site likely saved many thousands of dollars compared to purchasing costs. Additionally, the mulch's volume will substantially mitigate erosion over the next several years as the community has spread it thoroughly near priority areas since early November 2022. This demonstrates a well-orchestrated plan and incredibly efficient use of resources for EBM (Wellbrock & Bolte, 2019; Wong, 2016).

SUAS were incorporated to perform a flyover and establish the extent of damage from an above-ground perspective. This was impossible at the time with aerial or satellite imagery due to cost, availability, and access. However, it helped highlight another need for EBM: time-sensitive data. SUAS discovered the logging company illegally cut into property owned by the city and an adjacent homeowner. While this may have been possible using other means, sUAS help fill this niche by being readily deployable and cost-effective. Deploying on a moment's notice allows time-sensitive data to be captured and stored for immediate or temporal analyses. Since sUAS are used in time-sensitive disaster management, search and rescue, and real-time surveillance, the transition to EBM appeared organic.

Additionally, sUAS-generated products have established the site's baseline elevation, grades, and remaining structures and mitigated additional costs associated with a traditional land-surveying method. Several methods of acquiring imagery for EBM including satellite, piloted aircraft, and sUAS are discussed in the following sections with most having tradeoffs that outweigh the benefits of a small site location.

Strengths and Weaknesses of EBM

Strengths of Ecosystem-Based Management:

Ecosystem-based management (EBM) offers several strengths that contribute to its effectiveness in sustainable ecosystem management. First, EBM takes a holistic approach by integrating ecological, social, and economic considerations, providing a comprehensive framework that recognizes the interconnectedness of these factors. This approach allows for a more thorough understanding of the complexities of ecosystems and enables decision-making that promotes long-term sustainability (Wasson et al., 2015). Second, EBM emphasizes stakeholder engagement, facilitating inclusive decision-making processes and fostering collaboration among diverse stakeholders (O'Higgins et al., 2020; Wasson et al., 2015). This engagement promotes social acceptability, enhances the legitimacy of management actions, and helps balance conflicting interests. Third, EBM adopts an adaptive management approach, which allows for continuous learning, monitoring, and evaluation (Wasson et al., 2015. This adaptive nature enables managers to adjust strategies and actions in response to changing conditions, ensuring flexibility and resilience in the face of uncertainties. Finally, EBM emphasizes evidence-based decision-making by relying on scientific knowledge and data, enhancing the credibility and effectiveness of management strategies (O'higgins et al., 2020; Wasson et al., 2015).

Weaknesses of Ecosystem-Based Management:

Ecosystem-based management (EBM) also faces certain weaknesses that can pose challenges to its implementation. One of the primary challenges is the complexity introduced by the integration of ecological, social, and economic considerations. Balancing diverse objectives, trade-offs, and conflicting stakeholder interests can be a daunting task, requiring careful negotiation and compromise (Wasson et al., 2015). Another weakness of EBM relates to resource limitations, including financial constraints, limited expertise, and capacity (Olsen et al., 2006; Wasson et al.,2015). These limitations can hinder the effective implementation of EBM strategies and actions. Additionally, EBM encounters uncertainties and data gaps, which can limit the accuracy and reliability of assessments and decision-making processes. Addressing these uncertainties requires ongoing research, data collection, and monitoring efforts (O'Higgins et al., 2020). Furthermore, the development and implementation of EBM plans can be time-consuming, often requiring extensive data collection, stakeholder consultations, and adaptive management processes (Olsen et al., 2006).

(EBM) exhibits a balance of strengths and weaknesses that must be carefully considered to achieve effective and sustainable ecosystem management. The strengths of EBM, such as its holistic approach, stakeholder engagement, adaptive management, and evidence-based decision-making, provide a solid foundation for integrated and comprehensive management strategies (Olsen et al., 2006; Wasson, 2015). These strengths enable EBM to address the complexities of ecosystems and foster collaboration among diverse stakeholders. However, EBM also faces challenges, including the complexity of balancing diverse objectives, resource limitations, uncertainties, time-consuming processes, and compliance issues. Recognizing and addressing these weaknesses is crucial for successful implementation (Olsen et al., 2006). By capitalizing on its strengths while addressing its weaknesses, EBM can navigate the intricacies of ecosystem management, promote sustainability, and enhance the conservation and wise use of natural resources. Continual learning, adaptive approaches, and collaboration among stakeholders are key to effectively harnessing the potential of EBM for long-term ecological and societal benefits.

Situating the Problem

Anthropogenic disturbances to ecosystems frequently manifest within a range, stretching from positive to negative impacts. This spectrum becomes particularly evident concerning forests, as humans have historically depended on these natural resources for shelter, infrastructure, and diverse ecosystem services. Such a symbiotic relationship has sustained an enduring equilibrium, to which we owe profound acknowledgment. Regrettably, however, forestry operations, even at recognized locations such as Olympia's Cooper Crest restoration site, are frequently conducted sub optimally, leaving environments in a state of pronounced disruption. In the past, similar actions and collapses have caused the failure of entire countries and civilizations including but not limited to the Anasazi, Tiwanaku, Akkadians, Mayan, and Roman Empires (Diamond, 1994).

Clearcut logging serves as a poignant example of a profoundly destructive form of logging. Its repercussions are felt both immediately, with the initial devastation, and over the long term, through enduring ecosystem disturbances. Despite these ecological costs, clearcutting often yields the highest return on investment. The process allows for the swift extraction of valuable timber, leaving behind economically infeasible remnants as slash piles. These substantial biomass residues are typically incinerated rather than mulched, a practice that simplifies site clearance yet contributes to local and regional environmental concerns (Beck & Dobson, 2022; Gromicko, 2022).

Moreover, the decimation of ecosystems through clearcutting opens a gateway for invasive plant species to flourish, capitalizing on the scarred or compromised landscape. This proliferation of invasive species became the primary focus of our research. While clearcutting might be viewed as an outdated practice in the light of modern, sustainable methods, it epitomizes the typical compromises often visible along Washington's roadways (Sierra Club, 2023). It underlines the ongoing challenge of balancing economic gain with environmental stewardship in forestry operations.

Public vs. Private EBM

In the field of Ecosystem-Based Management (EBM), the involvement of both public and private entities is crucial for its successful implementation. Public entities, including government agencies and regulatory bodies, hold prominent roles in establishing policies, regulations, and frameworks for natural resource management. One such example is the Washington Department of Fish and Wildlife (WDFW), an active public entity engaged in EBM initiatives in Washington state. Collaborating with stakeholders, they develop comprehensive management plans that take into account ecological, social, and economic factors. Conversely, private entities, such as non-profit organizations, industry associations, and landowners, also contribute significantly to EBM through voluntary actions, partnerships, and sustainable practices. Notable private entities involved in EBM include The Nature Conservancy (TNC) and OlyEcosystems, who collaborate with public agencies, local communities, and industry stakeholders to implement conservation strategies. When comparing these entities, public entities possess legal mandates and regulatory authority, allowing them to establish and enforce EBM policies and regulations. Private entities, however, have more decision-making flexibility and can voluntarily adopt EBM principles according to their objectives. Additionally, public entities have access to public funds, providing them with resources for broader-scale EBM implementation, while private entities rely on diverse funding sources that may impact the scope and scale of their initiatives. Public entities operate within established legal and regulatory frameworks, whereas private entities adhere to voluntary standards and certifications related to EBM but lack the same regulatory power. In summary, while both public and private entities contribute to EBM, they operate within distinct contexts and frameworks, with public entities having a regulatory role and access to public funds, while private entities possess decision-making flexibility and diverse funding sources.

Public Entities in EBM

Public entities, such as government agencies and regulatory bodies, often play a prominent role in implementing Ecosystem-Based Management (EBM) initiatives. They are responsible for establishing policies, regulations, and frameworks for natural resource management.

For instance, the Washington Department of Fish and Wildlife (WDFW) is a public entity actively involved in EBM in Washington state. They collaborate with stakeholders to develop management plans that consider ecological, social, and economic factors (Washington Department of Fish and Wildlife [WDFW], 2023).

Private Entities in EBM

Private entities, including non-profit organizations, industry associations, and landowners, also participate in EBM efforts. They often contribute through voluntary actions, partnerships, and sustainable practices.

The Nature Conservancy (TNC) and OlyEcosystems are examples of private entities engaged in EBM. They work collaboratively with public agencies, local communities, and industry stakeholders to implement conservation strategies in Washington state (The Nature Conservancy, 2023).

Compare:

Decision-Making: Public entities typically have a legal mandate and regulatory authority to establish and enforce EBM policies and regulations. Private entities, on the other hand, tend to have more flexibility in decision-making and can voluntarily adopt EBM principles based on their own objectives.

Stakeholder Involvement: Public entities engage in extensive stakeholder consultation processes to ensure diverse perspectives are considered. Private entities often collaborate with stakeholders, but their engagement may vary based on their specific goals and partnerships.

Contrast:

Resources and Funding: Public entities generally have access to public funds, enabling them to allocate resources for EBM implementation on a broader scale. Private entities rely on funding from various sources, including grants, donations, and their own budgets, which can impact the scope and scale of their EBM initiatives.

Regulatory Frameworks: Public entities operate within established legal and regulatory frameworks, with the authority to enforce compliance. Private entities may adhere to voluntary standards and certifications related to EBM but may not have the same regulatory power.

Summarily, public entities have a regulatory role, operate within established frameworks, and have access to public funds. Private entities have more decision-making flexibility, rely on diverse funding sources, and may adopt EBM voluntarily. Both contribute to EBM but operate within different contexts and frameworks.

Contemporary and sUAS Ecosystem-Based Management

Though disturbances stemming from forestry are often unavoidable even when focusing on sustainability, the economic drive to continue logging exists and will continue to exist for the foreseeable future. Due to unsustainable forestry practices, like those at Cooper Crest, EBM evolved out of the need for multidisciplinary efforts to solve these complex problems. Grounded in adaptive management theory, EBM offers a flexible and experimental avenue towards managing and modifying ecosystems based on public needs and sustainability for future resource availability. EBM essentially incorporates local private and public stakeholders to generate a viable action plan. In phase I, policymakers/ decisionmakers incorporate all the stakeholders' chief concerns and values into a formal program. Concisely, research is then conducted during phase II, to attain knowledge and abide by regulations used in phase III's EBM Plan, which is implemented, monitored, and evaluated during phase IV. Additionally, each phase may revert to any previous phase due to regulatory, land use, or other unforeseen changes or extenuating circumstances that require such action.

However, EBM's largest faults occur within the technological realm or accessibility to professional tools (Curtice et al., 2022). As a result, resource managers relying on EBM's foundational concepts and tools face mounting frustration regarding funding, the application of devices, and the interdisciplinary utilization of contemporary technology. In addition, the process often takes years, with new and critical projects reappropriating funding based on public or private interest and support. However, technology has great benefits when applied within an EBM context.

Recently, contemporary EBM is heavily leveraging technology to augment its capability to monitor and manage various ecological aspects, such as invasive species management. One of the emerging technologies in this domain is the small-unmanned aircraft system (sUAS), or drone, which offers promising potential for transforming EBM practices.

SUAS can be equipped with a variety of sensors to collect high-resolution spatial and temporal data that are integral for effective EBM. For instance, sUAS can provide rapid assessments of vegetation health and changes in biodiversity through high-definition photography and videography, multispectral imagery, and LiDAR scanning (Anderson & Gaston, 2013). Furthermore, the deployment of drones for monitoring purposes is non-intrusive and has minimal impact on the ecosystems being surveyed (Vierling et al., 2011).

The use of sUAS in EBM also provides advantages in terms of cost and accessibility. SUAS are considerably cheaper than piloted aerial vehicles, enabling more frequent and broader data collection (Huang et al., 2015). Moreover, sUAS can access remote and challenging terrains that are difficult or risky for human investigators to reach (Hardy et al., 2017).

However, while the usage of sUAS in EBM holds great potential, there are still challenges to address. Regulatory constraints, technical proficiency requirements, data management issues, and privacy concerns are among the factors that must be considered when integrating sUAS into EBM strategies (Koh & Wich, 2012). Principally, the integration of sUAS into contemporary EBM opens up new avenues for ecological monitoring and conservation. The broad spectrum of sUAS applications, combined with the cost-effectiveness and ease of accessibility, make these systems an invaluable tool for ecosystem management in the modern era.

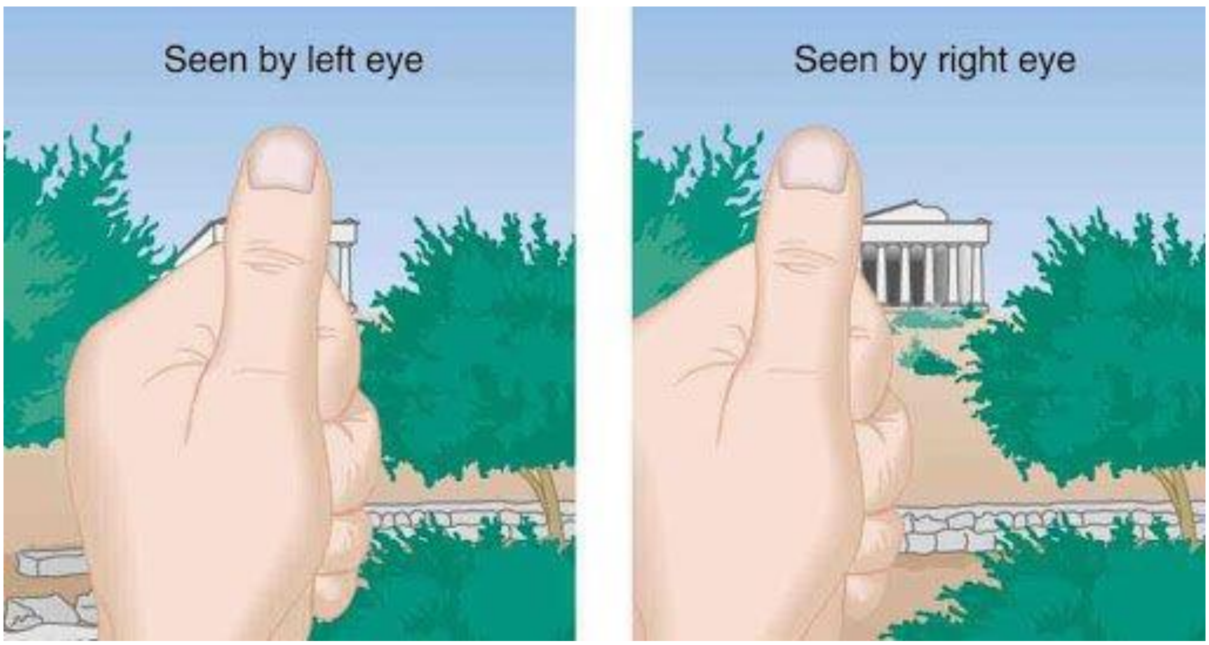
Remote Sensing Theory

Remote sensing measures a surface without physically touching or making contact (Duke University, 2019; Haldar, 2018). There are several types of remote sensing; however, this research focuses on applying an inexpensive standard RGB camera mounted to an sUAS. RGB cameras use scattered and reflected visible light between approximately 400 and 700nm to gain insight into phenomena for spatial analysis in geographical information systems (GIS) (Agarwal, 2004; Asenova, 2018; Haldar, 2018).

The pictures, or imagery, attained using an RGB sUAS-mounted camera are measured with a method of triangulation called parallax. Parallax, or stereoscopic parallax, is the observing and measurement of phenomena from different perspectives (Haldar, 2018). While the GIS algorithmic process is complex, the fundamentals of parallax are known to most people with a simple experiment (See Figure 3 below).

Figure 3

Parallax Experiment



Note. Remote sensing platforms use parallax in the same way as many organisms. The perspectives from each eye allow for depth perception and distance measurement. Performing the simple experiment in this image demonstrates the core theory behind parallax and triangulation (Joyce Project, n.d.).

Image Acquisition Methods

In several examples, scientific and industrial practices are evolving geospatial frameworks away from relying solely on satellite, piloted -aerial, or manual terrestrial surveys (Asenova, 2018; Martinez et al., 2021). Incorporating sUASs into science and industry already benefits agricultural monitoring, corridor monitoring, and architectural inspections thanks to recent innovations in sUAS technology (Carabassa et al., 2021; Malecha, 2019). These innovations include low cost, rapid deployment time, high spatial resolution quality, short flight time, hasty revisit cycle, easy operation, and georeferencing using GPS devices (Asenova, 2018, Carabassa et al., 2021). However, along with these improvements, various professional accessories and UAV models can escalate costs by $200,000 and require special licensure to operate in the U.S.'s national airspace (FAA, 2022; Malecha, 2019). Furthermore, other gate-keeping forms such as educational requirements, monthly technology subscription services, training, policy navigation, and other site-specific considerations impact the technology and the feasible methods (FAA, 2022).

In good and especially uncertain times, affordability is a principal variable requiring discussion that is extremely site specific, however sUAS may bring great value to small or medium sized sites with regards to resolution and precision, even with severe constraints. Conducting research at Cooper Crest motivated this research initially because of the potential for cost savings and deployment time compared to traditional surveying methods. Using EBM theory, the Cooper Crest site collaborates with the local colleges and professionals to get surveying products at a free or extremely reduced cost.

Image Acquisition Costs

Paid surveying methods range from $75 an hour for sUAS to several thousands of dollars for piloted aircraft or a land survey. Some surveyor teams charge by square foot within an average range of 15 to 70 cents per foot while many charge based on property sizes (HomeGuide Team, 2023). The Cooper Crest site is around 23.5 acres for example. Potentially adding to a similar site’s costs are topographical and other precision requirements. It is also important to note that a traditional aircraft or ground survey requires a team of individuals, often three or more, which may charge up to $225 per hour or more each. While aircraft and satellites can cover large expanses, they usually have minimum size requirements for high-resolution taskings and paid office staff with additional pay requirements

(Skywatch, 2022). Piloted aircraft surveys often charge upwards of $120 per acre for high-resolution taskings as well. At a small restoration site like Cooper Crest or other public projects, EBM offers a unique collaboration opportunity with the community, including, for example, The Evergreen State College (TESC), that allows for near-complete mitigation of many associated costs and presents an opportunity for furthering environmental research with a living laboratory while also teaching valuable skills to the next generation of professionals.

When comparing the costs of using sUAS, satellite imagery, and piloted aircraft surveys for various applications, several factors need to be considered:

Data Acquisition Costs:

- sUAS: The costs associated with sUAS include the initial investment in equipment (drone, cameras, sensors), maintenance, and operator training. However, sUAS tends to be more affordable than piloted aircraft in terms of acquisition costs.
- Satellite: Satellite imagery is typically obtained through satellite service providers. The costs depend on factors such as image resolution, coverage area, and frequency of acquisition. Satellite imagery can vary in price, and high-resolution imagery tends to be more expensive.
- Piloted Aircraft Surveys: Using piloted aircraft for surveys incurs significant costs, including aircraft rental or ownership, fuel, pilot salaries, and maintenance. The costs can be substantial, especially for large-scale or frequent surveys.

Coverage and Resolution:

- sUAS: sUAS offers the advantage of high-resolution data acquisition over small areas. They are well-suited for detailed mapping and monitoring tasks at a local or site-specific scale.

- Satellite: Satellites provide extensive coverage and global accessibility. However, satellite imagery may have limitations in terms of resolution and the frequency of image updates.
- Piloted Aircraft Surveys: Piloted aircraft can cover large areas, but the resolution may be lower compared to sUAS or satellite imagery. However, they offer the flexibility to fly over specific locations as needed.

Data Processing and Analysis:

- sUAS: Data processing and analysis can be conducted using readily available software and tools. The costs associated with these processes are relatively low compared to other methods.
- Satellite: Satellite imagery may require more advanced software and expertise for processing and analysis. Additional costs may be incurred if specialized software or remote sensing experts are needed.
- Piloted Aircraft Surveys: Data processing and analysis costs for piloted aircraft surveys can vary depending on the complexity of the data and analysis requirements. Advanced software, skilled analysts, and additional processing time may be necessary.

Operational Flexibility:

- sUAS: sUAS provides greater flexibility in terms of deployment and can be easily maneuvered in challenging terrains or areas with limited accessibility.
- Satellite: Satellite imagery is acquired based on pre-determined schedules and may be affected by cloud cover or other atmospheric conditions. It offers less flexibility in terms of specific timing or target areas.

- Piloted Aircraft Surveys: Piloted aircraft surveys provide flexibility in terms of target areas and timing of data collection. They can be flown on-demand and adjusted according to specific project needs.

It is important to note that the costs associated with sUAS, satellite imagery, and piloted aircraft surveys can vary widely depending on the specific project requirements, scale, and geographic location. Conducting a thorough cost-benefit analysis, considering the specific needs and constraints of the project, is crucial in determining the most cost-effective and suitable option.

Satellites

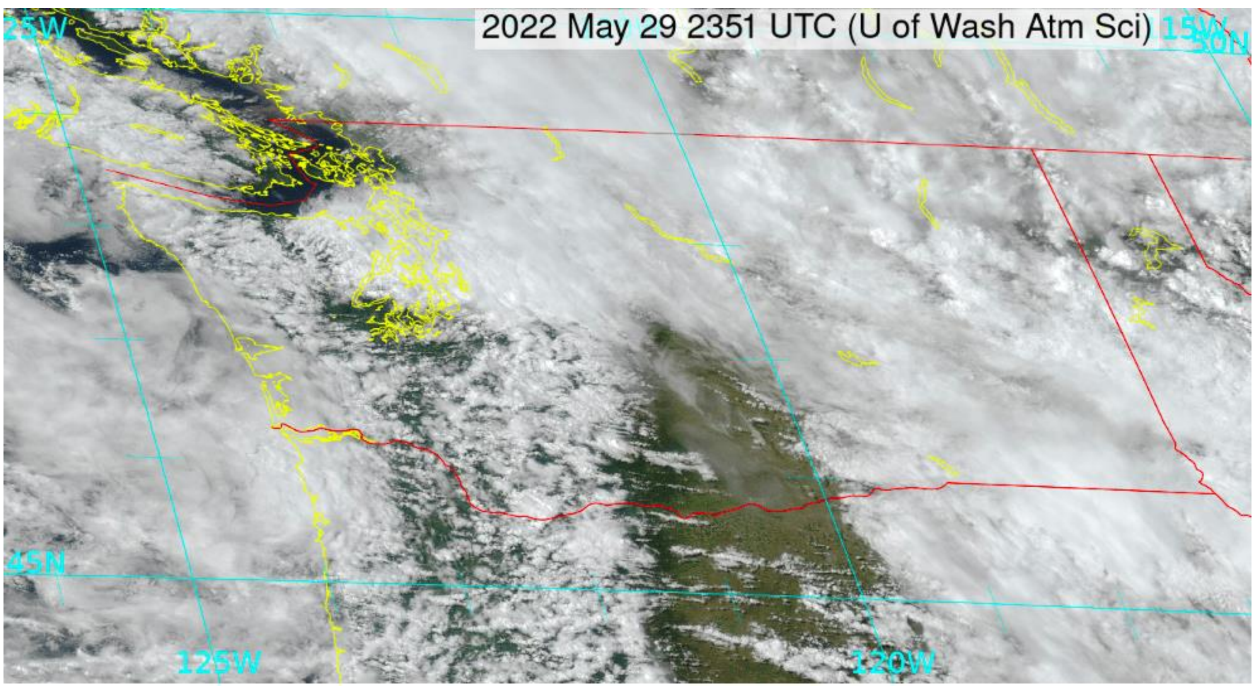
Since the first satellite photo of Earth on August 14, 1959, satellite technology has rapidly taken on an integral role in modern civilization. These roles include national defense, public safety, economic support, emergency management, public health, and environmental monitoring (Canadian Space Agency, 2013). In 2008, the USGS advanced these roles by granting free public access to LANDSAT or remotely sensed satellite imagery (U.S. Geological Survey [USGS], 2018). Previous to 2008, LANDSAT imagery ranged from $200 per RGB image to $4000 for multispectral band imagery (USGS, 2018). However, free LANDSAT data often lacks sufficient resolution to effectively inform EBM on specific sites.

Resolution for most satellite imagery varies widely as the pixel size or most negligible unit of measurement ranges from 30 to 30 meters resolutions between two and five meters per pixel (Maxar Technologies, 2022). However, high-resolution satellite images are purchasable for approximately \$20/km^2 with pixel sizes ranging from around 30-70 centimeters per pixel, a 100-time resolution increase (Maxar Technologies, 2022; Skywatch, 2012). Due to scale, satellite imagery often suffices for large-scale projects such as agricultural or regional mapping (Martinez et al., 2021). However, for smaller locations, such as the roughly 23-acres Cooper Crest site, other methods, such as sUAS, are more effective at determining granular effects and revealing temporal change at high resolutions (Martinez et al., 2021; Skywatch, 2022). Additional issues regarding satellite incorporation into environmental monitoring are the temporal gaps between imaging that can be months or years apart and the presence of cloud cover.

Performing a temporal analysis is possible using satellite imagery. However, satellite images containing clouds or those acquired in winter months may cause months of data to be unusable. During the winter, the solar zenith angle (SZA), or sunlight, is low on the horizon; this negatively affects scientific studies and remote sensing platforms' ability to gather enough light to form a rigorous image (Ma et al., 2020). In addition, the study's latitude, or distance from the equator, compounds this effect.

Figure 4

Satellite Cloud Sample



Note. May 29, 2022, cloud cover over the west coast and Puget Sound can affect data by creating temporal gaps. During the winter months in Washington, satellite imaging is unreliable at best (University of Washington, 2022).

Higher resolutions innately carry more information, or data, within each pixel. For example, a five-by-five-meter resolution may be sufficient to locate more prominent features or large-scale changes. However, this resolution will not examine minute changes such as seedling death, erosion, or identifying their geospatial location. While satellite-produced imagery is accessible, free, or relatively inexpensive, other methods, such as sUAS or aerial surveys, offer additional benefits while accounting for several tradeoffs in resolution and temporal analyses.

Crewed Aerial Surveys

In 1858, Gaspard-Felix Tournachon, better known by his alias "Nadar," took the first aerial photograph while floating over Paris, France, in a hot air balloon. Since then, aerial surveys have grown with technological advancements, including balloons, sUASs, and helicopters. However, for the remainder of this thesis, aerial surveys will exclusively define flight operations conducted with airplane-mounted equipment unless otherwise noted. Aerial surveys, like satellites, have a long history of use for geographical and ecological practices and are not without their tradeoffs. These tradeoffs often include spatial resolution, swath width, and flight altitude (Klemas, 2014).

These tradeoffs are intrinsically tied to one another. For example, lowering the altitude of an airplane will increase resolution; however, it will also increase the number of passes needed to cover a large site (Klemas, 2014). Conversely, increasing altitude decreases resolution and the number of passes over an area. The SZA also affects the choices for an aerial survey as the low angle subsequently lowers the inherent brightness of the scene (Valencia et al., 2021). A darker location will increase the exposure time needed, as will the sensor sensitivity and velocity of the aircraft.

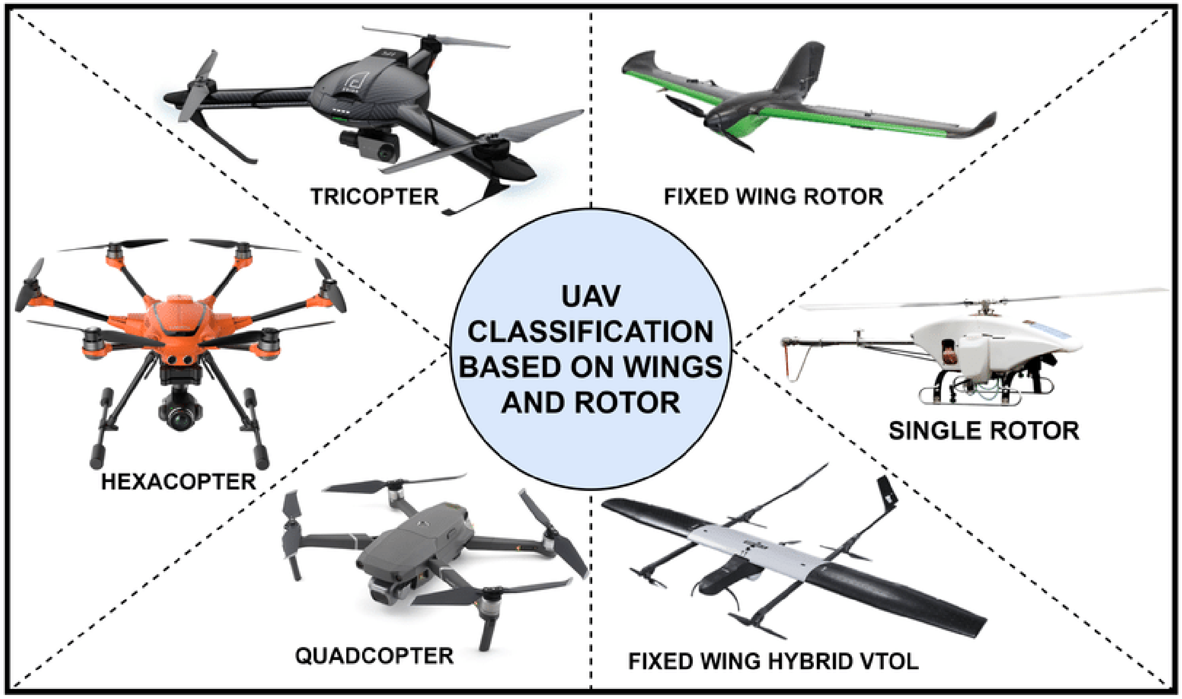
Additionally, choosing an airplane to photograph a site may be impractical due to costs and selection. For example, the Cooper Crest site is small, at around 23 acres, and would not warrant an aerial survey. However, in March 2021, the City of Olympia paid for a flyover of the entire city, including georeferenced images in the RGB and I.R. spectra. This imagery was made available for this project however, it fell outside of the scope of this research.

sUAS

The Code of Federal Regulations (CFR) and the Federal Aviation Administration (FAA) recognize sUAS as being an autonomous, unmanned aircraft that weighs less than 55 pounds at takeoff (Small UAS Rule, 2012). Different types of sUASs and UAVs are increasingly prevalent in many scientific fields and industries. However, EBM has yet to fully amalgamate sUAS to its full potential (O'Higgins et al., 2020). There are four common types of drones: multi-rotor drones, fixed-wing drones, fixed-wing hybrid vertical takeoff and landing (VTOL), and single-rotor drones (see Figure 5 below). The agriculture industry is a strong proponent of autonomous flight because of the numerous models and benefits associated with autonomous sUAS flight (Colomina & Molina, 2014; Garcia-Haro et al., 2022). This is especially true for fixed-wing and high-capacity quadcopters that offer more range and longer flight times than smaller consumer or prosumer sUAS models. In general, sUAS-produced imagery and workflows are increasingly helpful for monitoring and spatial analysis in EBM (Lee et al., 2016; Martinez et al., 2021).

Figure 5

Standard Classification of UAV Models



Note. This figure depicts the common types of UAVs. In addition, this figure further distinguishes multirotor UAVs into common subclasses based on the number of rotors (Chamola et al., 2020). Different models have various tradeoffs, such as takeoff, flight time, load-bearing capacity, and size.

Environmental monitoring and spatial analysis using sUAS-produced imagery are practical tools for time-based mapping change and EBM minutia (ESRI, n.d.). SUAS gathered imagery provides high-resolution products, including digital elevation models (DEMs). DEMs use parallax triangulation and sUAS metadata to build models of elevation change on a worksite's ground or uppermost surface. Different models within DEM include digital surface models (DSMs) and digital terrain models (DTMs). A DSM measures the uppermost surface of the site to include natural and human-made features versus a DTM that records only the ground elevation (ESRI, n.d.). EBM relating to forestry incorporates all these models and variations for specific workflows. An example of one workflow is a canopy height model (CHM) or digital height model (DHM) that measures the canopy height by subtracting the DTM from the DSM. Rather than determine the elevation of the surface or terrain, this model shows the approximate average canopy height. Additional cost-saving and temporal products, such as orthomosaics created by sUAS, are gaining traction in engineering and EBM.

An orthomosaic is a collection of imagery stitched together using complex algorithms within processing software. The software incorporates the parallax and locations of pixels from adjacent imagery to create a relatively seamless model of an entire worksite. Generating these products allows for constructing 2d and 3d models for spatial analysis, such as the Python-based deep learning tools created by ESRI Indonesia.

Python-Based Deep-Learning Model

Deep learning models and neural networks have recently become mainstream with the recent release of chatGPT and the newest iteration of G.P.T. 4, released in early 2023. Deep learning models have the potential to perform various tasks, including advanced GIS spatial analysis, such as training from manual image classification, object detection, semantic segmentation, and land-cover mapping. For example, deep learning models can be trained on high-resolution satellite imagery to automatically identify and classify land cover types, such as urban areas, forests, and agricultural lands. Similarly, deep learning models can be trained on sUAS or other aerial-derived imagery to detect and classify invasive species in landscapes. This intersection between EBM and deep learning is what inspired this project. Additionally, ESRI has already developed software and architecture that further streamlines its implementation into this and future research. However, it does not specify how and what hyperparameters to incorporate.

My thesis research explores the potential of sUAS deep learning as a spatial science tool to understand the real-world relationships between the constraints encountered in land management and how technology may benefit them using EBM as a guide. As noted previously, EBM is a complicated and often expensive process. Phase IV is the last phase. However, with EBM being a system thinking model, phase IV can result in constant modification and experimentation back to any phase. Monitoring, the most expensive and time-consuming part of phase IV, means that mitigating the financial and temporal impacts will benefit EBM the most. Undoubtedly, sUAS may benefit all of EBM. However, this research seeks to identify and monitor invasive species at a database sampling location. Typically, sUAS flight missions take less than an hour, plus a few hours of processing time. Historically, gathering this data took days to weeks, manually monitoring trees for animal predation, blowdowns, or other purposes. Processing does take significant blocks of time. However, after establishing a modeled workflow and a thoroughly trained database, deep learning requires little input or editing. Additionally, the deep learning packages within the ESRI suite are fully shareable in a small DLPK file extension.

Deep learning models already benefit agricultural production with tools like crop yield prediction using historical analyses, pest detection, soil analyses, precision agriculture, and efficient harvesting techniques. This research transforms these models into invasive image recognition, geospatial analysis, early detection, and distribution modeling using the same fundamental agricultural industry concepts. This research sought to eliminate several tradeoffs by incorporating a previously designed deep learning model in the ArcGIS Pro platform. Choosing this method limited the computational expenses and vulnerability to manipulation while maintaining substantial customer support. This was rather important as I, the author, have extremely limited coding capabilities and seek to make this model as replicable as possible.

However, given the potential of deep learning models, several drawbacks exist. Most notable are the data amounts and resolutions needed for proper identification. In addition, the model is only as good as its trained input. There is always the threat that incorporating low-resolution imagery may ruin the entire database, especially over the timeframes of this research and its geographical location. Another drawback stems from the black-box nature of deep learning models. Performing experiments with a model that is difficult or impossible to understand may prohibit replicability and decrease authoritativeness. However, many machine learning or A.I. deep learning models are black boxes, with a few engineers understanding the neural network or hyperparameter selections a model incorporates. Additionally, the model may not transfer to other site locations because numerous Z variables may skew the results.

Deduction

Historical ecosystem management methods are often ineffective at addressing multi-scale linkages because of a lack of multidisciplinary expertise and an inability to manage the whole matter. Adaptive management and EBM are functional paradigms that address site-specific issues with a structured format that allows on-the-fly learning and adaptation. However, despite their many benefits, some tradeoffs often stem from inclusivity in decision-making and maintaining expert advice in dynamic and complex systems. Spatial analysis with current technologies such as satellite and aircraft have proven effective in the past. However, there are also tradeoffs when using these technologies, such as cost, temporal analysis, and timeliness. As a result, sUASs of all sizes are increasing in effectiveness around the globe.

This research seeks to use affordable sUAS technology with precision GPS to achieve a baseline for the Cooper Crest site using established spatial analysis methods. By incorporating a used prosumer DJI Phantom 4 Version 2.0 with an RGB remote sensor, I intend to offer a replicable and affordable model for NGOs and other interested parties to incorporate. The technology used in this research costs less than $5000. However, it has a high threshold for training and is rather technical. This research addresses several drone-related roles that will likely benefit phase IV's costly implementation, monitoring, and evaluation.

Experts predict that climate change coupled with anthropogenic disturbances will increase the number and size of forest fires throughout the year, and especially during the potentially extended regional fire seasons (Reilly et al., 2022). The coupling of this effect with unmanaged invasives, such as Scotch broom, may create a regional recipe for disaster. Ultimately, anthropogenic disturbances such as deforestation and reforestation demand innovative scientific ecosystem research and biodiversity assessments using EBM (Asenova, 2018).

Integrating ESRI Indonesia's Python-based deep learning or machine learning for sUAS and satellite imagery during the low SZA may offer insight into local EBM and situation-dependent methods for identifying invasive Scotch broom during the sUAS flying offseason. In addition, this model may include the best-use cases for the utilized technology typically restricted to other industries and seasons. Ultimately, reducing costs and time spent for land managers with a descriptive framework will reduce time on-site, reduce costs, increase overall EBM efficiency, and possibly reduce associated burnout from a less informed management plan. I predict that sUAS will have its tradeoffs during the winter, but there are minimal studies incorporating low-cost and easily accessible models that directly address these types of concerns. Therefore, the rest of this research focuses on the data collection, model development, and overall discussion of deep learning and sUAS effectiveness within EBM.

4. Methods

Roadmap

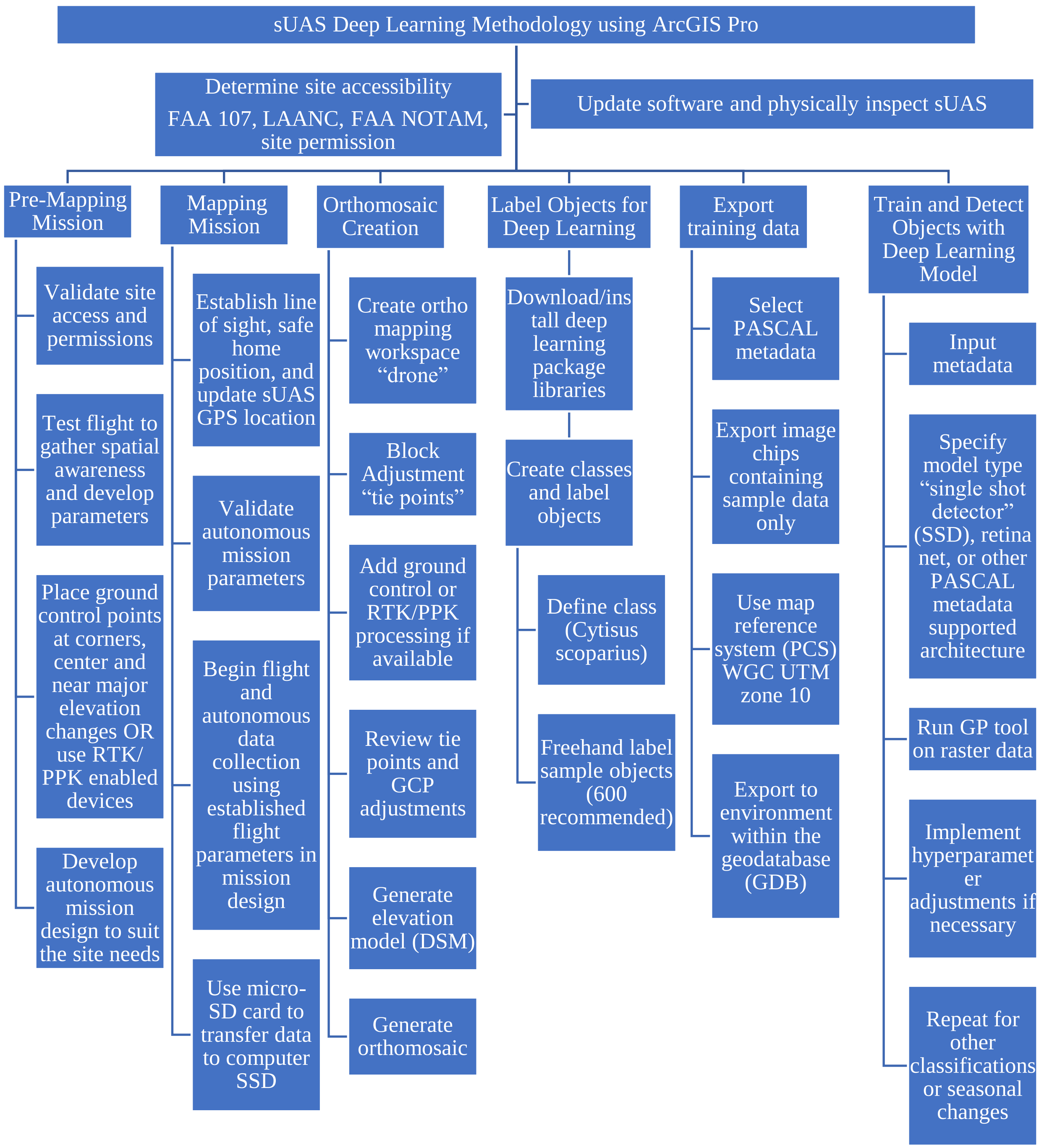
The methods section for this thesis is composed of six main areas. First, *data collection* for this research began in August 2022 using an iPhone XR, iPad Pro 12.9, DJI Phantom 4 Pro V2.0, and a Juniper Geode GPS unit for GPS additions. Second, *Cytisus scoparius* (Scotch broom) and other precision data were acquired using a combination of aerial, GPS, ground-truthing methods, and ESRI's Survey123 application at Cooper Crest, but not the database site. Third, I used ArcGIS Pro, Drone2map, and WebODM to *prepare* the Scotch broom and Cooper Crest spatial layers for analysis and object identification. Fourth, a *deep-learning model* developed by ESRI Indonesia was *evaluated* and then *deployed* using the Scotch broom data as a proof of concept. Fifth, a model was next *validated* using ground-truthing and software methods. Sixth, *model refinement and interpretation of results* regarding the initial thoughts on the model's effectiveness conclude the methods section.

Additionally, many of the products created from the methods section are essential to the refining and deep learning research process. In that regard, the imagery from these steps lies in the results and discussion sections, where it can be discussed and critiqued. This was important because of the many constraints placed on this research. For example, limitations include incorporating as many default settings as possible using the ArcGIS Pro workflows to simplify the operations. Below is a graphic depiction of the steps from mission planning to the training and utilization of the model itself in general order:

Data Collection

Figure 6

Conceptual Model of sUAS and Deep Learning Workflows



Note. The conceptual model of the sUAS supported mapping and deep learning workflows.

Materials and Equipment

Ground control points (GCP), GPS locational data, and ground truthing were collected and processed using the following:

- Juniper Systems Geode single band GNS3S GPS receiver
- iPad 12.9 or iPhone with current iOS
- ESRI Survey123
- ESRI Fieldmaps
- ESRI drone2map and ArcGIS Pro

I obtained aerial imagery using the following equipment and software:

- DJI Phantom 4 Pro v2.0 with a Thor's World iPad mounting controller bracket for 8–13-inch tablets
- A 2nd generation iPad Pro 12.9 running an updated iOS
- iOS applications DJI Ground Station Pro (G.S. Pro) and DJI Go with the most current updates

Digital processing took place using the following computer and software specifications:

- H.P. Omen laptop running Windows 11 with BIOS F.09-04/24/2019
- NVIDIA GeForce GTX 1060 with Max-Q Design, 6GB DDR5 VRAM
- 32 GB of DDR4 system memory
- Intel(R) Core (TM) i7-8750H CPU @ 2.20GHz
- Survey123 mobile and desktop applications
- Field Maps mobile and desktop applications
- Drone2map desktop drone imagery processor

- ArcGIS Pro for pre, post, and final processing. Drone2map software errors will favor ArcGIS Pro from all data gathered after November 2022.
- Adobe Creative Cloud suite for videography

Aerial Imagery Acquisition Approach

A stock DJI Phantom 4 Pro V2 using an RGB remote sensor gathered all aerial imagery used for this research (see Figure 7, below). The remote sensing system mounted on this platform used a standard 4k resolution 20-megapixel camera mounted on a 3-axis gimble (pitch, roll, and yaw). This model sUAS was effective in large part to the camera specifications.

The Phantom 4 Pro camera's specifications optimally supported a ground sampling distance of approximately 1-5 cm per pixel while simultaneously flying missions at safe heights between 75 and 250 feet above ground level (AGL). A ground sampling distance (GSD) is the length of the line drawn between the center of two adjoining pixels on a digital orthomosaic. An orthomosaic is a collection of orthorectified images that are combined and distorted slightly to match the map projection's geometry while removing distortions from the camera and platform. The variables used to calculate the GSD included the height of the sensor above the terrain or objects and the camera's image width, sensor width, and focal length.

This camera’s decent image width, focal length, and sensor width allowed this sUAS to fly at higher and often safer altitudes while maintaining a high-resolution GSD between 1 and 5 cm/pixel. Creating a high-resolution GSD was also essential to efficiently train the deep learning model (see Figures 8 and 9 below).

Figure 7

DJI Phantom 4 Pro v2.0

Note. Stock photo of a DJI Phantom 4 Pro v2.0 courtesy (Abbott, 2020)

The total hours flown for this research were approximately 90 between the mapping and video documentary missions. These missions resulted in over 3000 individual jpeg images and tens of hours of 4k 60 frames per second (fps) video. In addition, for each flight, pre, during, and post-inspections were conducted on the aircraft to ensure safe and reliable operations per the manufacturer's recommended standards and the FAA's best safety practices (DJI, 2021; FAA, 2022). The sUAS's remote controller (RC) was attached to an iPad Pro 12.9, running one of three apps depending on the mission:

- DJI Ground Station Pro (G.S. Pro). This free application saved preprogrammed missions and flight patterns. This application was paramount to this research's replicability in creating safe, effective, and rigorous mapping missions. Unless otherwise noted, G.S. Pro was the primary application for all mapping efforts.

- DJI GO. This application permitted manual flight during videography missions and the Scotch broom database development. Although this is an entry-level application for learning to fly, mastering this software was vital to employ G.S. Pro successfully.
- ESRI SiteScan LE. This is the accessible version of ESRI's SiteScan application on the iPad. This program does an excellent job of mission planning and has a terrain follow function that ensures relatively stable GSDs. One drawback is that this application does not allow the sUAS to stop while taking a photo. While it gets missions completed more efficiently, there is also the possibility of the imagery having a motion blur. Thankfully, the Phantom has a mechanical shutter that significantly reduces motion blurring.

Cooper Crest Aerial Mission Design

I planned and conducted safety inspections of the aircraft, locations, and personnel for all missions. In addition, before planning flight missions or stepping foot on the property, I obtained a safety liability waiver from the property owner, OlyEcosystems. Establishing communication with the site owner and learning about their mission helped to inform how my research, the college, and OlyEcosystems goals aligned and intersected with EBM theory (O'Higgins et al., 2020).

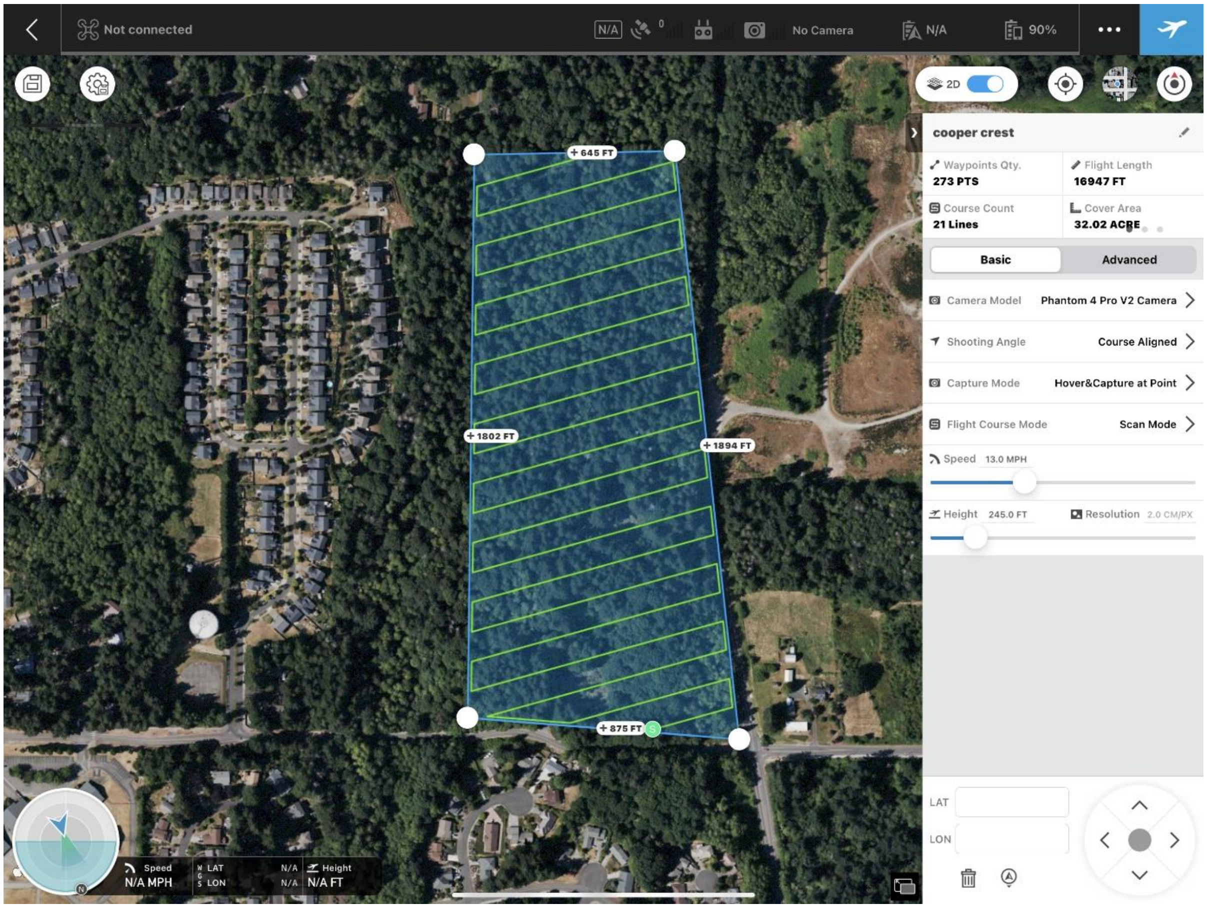
I established the systematic flight mission plan after conducting the preliminary site visit in August 2022 and with the parcel boundaries from Thurston County. The mission parameters loosely followed Cooper Crest Road to the east, 20th Avenue to the south, and the property boundaries to the west and north. There were no temporary or permanent flight restrictions within the confines of the study.

I used the onboard location sensors of the drone and DJI Go's user interface (UI) to determine safe flight altitudes, including the return-to-home height. The return to home and mission altitudes were entirely site dependent at approximately 300 feet above ground level (AGL) and no less than 125 feet AGL.

The resulting study location was 32.02 acres, including two private parcels within, and consisted of a 21-line lawnmower pattern flight grid. Each resulting mission over Cooper Crest averaged 272 top-down perspectives (nadir) photos in the 26 minutes and 56 seconds it took to fly the 16,947-foot mapping route. Additionally, each mission required approximately two batteries to fly at 245 feet A.G.L. with front and side photo overlap ratios of 75%. Manipulating these degrees of freedom helped achieve the 2-5 cm GSD goal (See Figure 8 below).

Figure 8

Cooper Crest Recurrent Flight Missions



Note. This screenshot of the author's iPad G.S. Pro application shows the basic lawnmower flight pattern designed for the Cooper Crest case study location (2023). A small yet important detail is that the DJI Phantom 4 Pro v2.0 uses a mechanical camera shutter. Rather than an electronic shutter that increases the distortion from movement, a mechanical shutter is rapid and prevents motion blur seen with many other sUAS models. Even with a mechanical shutter, image quality is superior when choosing the hover and capture-at-point feature. Again, this creates a trade-off by slowing the mission; however, the altitude and camera quality help mitigate this additional time to be negligible.

For the flight missions, a 2-5 cm GSD was deemed acceptable in terms of resolution and allowed for spatial analysis using the ESRI suite of products. Trade-offs were associated with choosing a GSD (See Figure 7 above). For example, flying at higher altitudes would result in faster missions; however, the resolution would suffer. Likewise, flying at lower altitudes with the required photo overlap of 75% would use seven or more batteries, large quantities of data, thousands of images per mission, and unrealistically increased flight times. While the increased resolution may be necessary depending on the context of an EBM issue, this case study did not require higher resolution. Therefore, an approximate 5 cm GSD goal was deemed acceptable for flight and computational processing times.

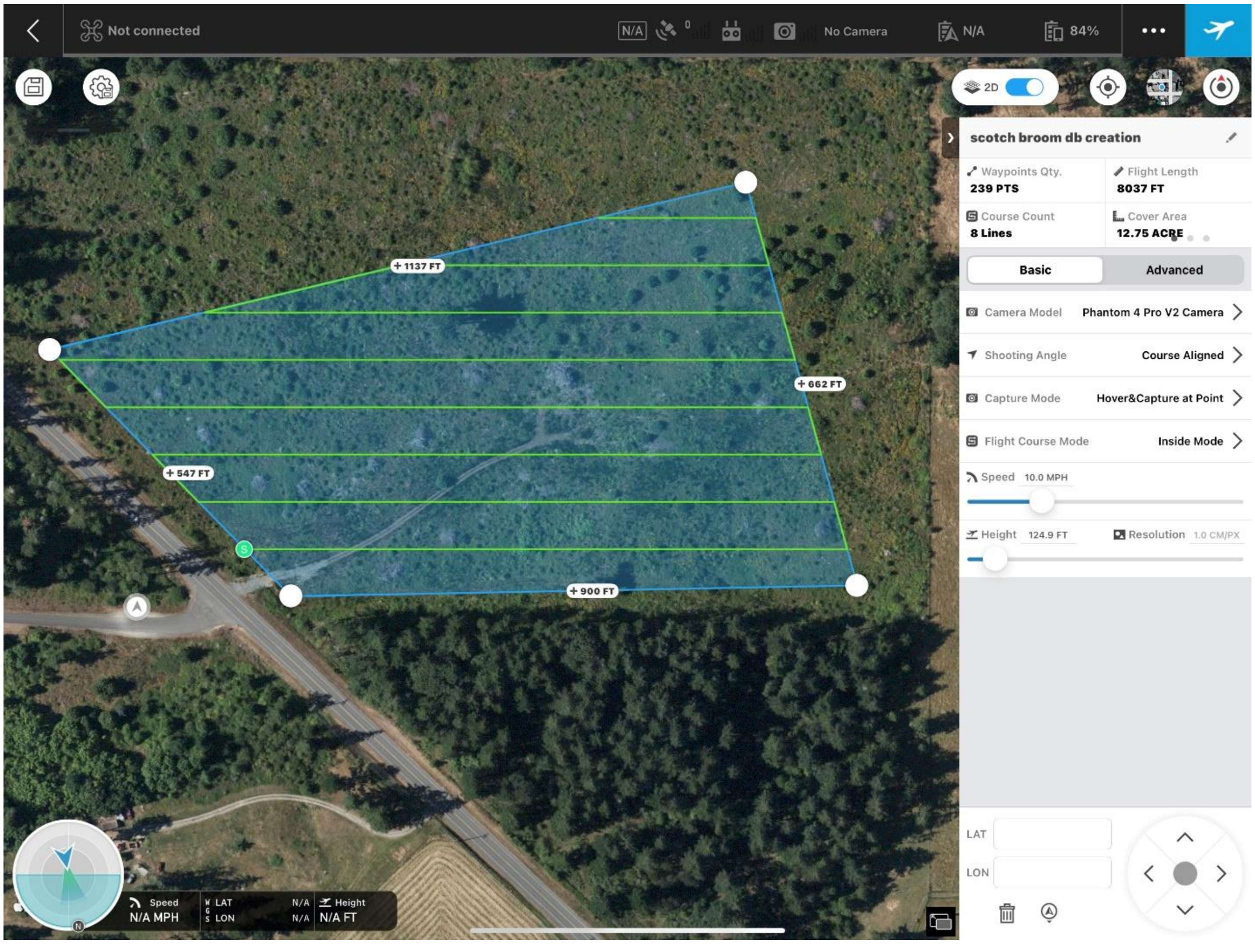
Invasive Database Mission Design

The development of the invasive species database used many of the same conditions surrounding the Cooper Crest flight mission's development. The resulting invasive mission consisted of just under 13 acres, with around four central acres flown for each flight. Depending on the height and overlap ratios, these flights acquired between 239 and 310 photos per flight. Given that Scotch broom is a successful invasive species, locating a heavily infested area off the local highways was not difficult. Seasonal weather in the Pacific Northwest played the most significant role in choosing a site close to home and with publicly available sUAS takeoff space on short notice. A recently deforested private location within 10-15 minutes of my house and with public takeoff access was determined as the best fit given the constraints of the research (See Figure 9 below).

Ground truthing procedures and GPS correction were not incorporated into the invasive database. While it may have benefited this research, both can add high costs for an organization. This would have made locating a site significantly more complex and remained outside the scope of this research. Additionally, creating the database for the deep-learning model did not require GPS correction. The model uses pattern recognition from human training inputs without recognizing the location's precise x, y, or z values. Instead, the model calls for a high-resolution image with several hundred examples to build upon for ideal operations (Abdilah, 2021).

Figure 9

Invasive Database Flight Mission



Note. This screenshot of the author's iPad shows the basic parameters for creating the Scotch broom mission (2023). This mission uses a 1.0 cm/pixel GSD goal to train the deep-learning model, highlighting the trade-offs associated with increasing resolution. Flying at a lower altitude significantly increased the number of images needed. To mitigate this effect, a lower side overlap ratio of 60% mitigated the increase in images and time for the mission while maintaining the 1.0 cm/pixel GSD goal. Even with mitigation, it is essential to note that this site is 20 fewer acres than Cooper Crest, which still requires 238 unique image captures.

GPS and GCP Incorporation

When applicable, a Juniper Geode GNS3S single-band GPS unit provided necessary precision GPS accuracy within submeter ranges (See Figure 9 below). The Geode is a rugged, open interface platform with scalable accuracy levels depending on the GPS network availability. For this research, the Geode synchronized to a free network of satellites that maintained a circular error probability (CEP) accuracy within the abovementioned ranges. CEP is the circular measurement from a known point that contains approximately 50% of the GPS values recorded, as shown in Figure 10 below. The Geode greatly assisted with GPS correcting several orthomosaics at the Cooper Crest site; however, it was not used for most of the database research to simulate not having safe terrestrial site access.

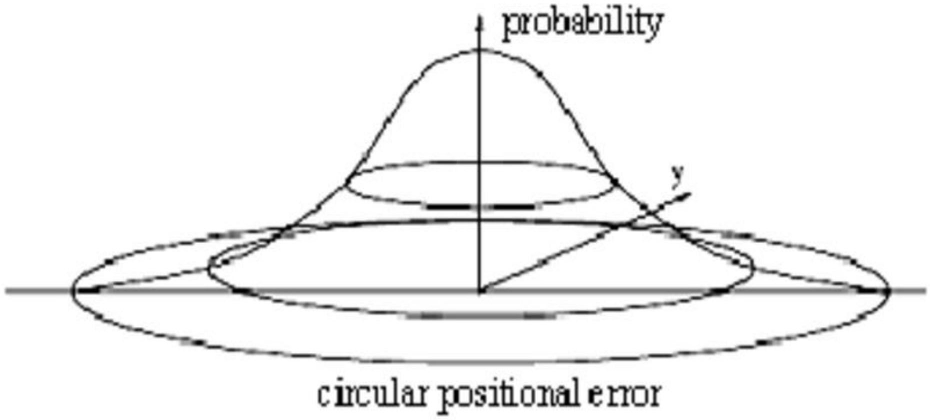
Figure 10

Juniper Systems Geode GNS3S

Note. Stock photo of Juniper Systems Geode GNS3S precision GPS device courtesy of (Blickenstorfer, 2023).

Figure 11

Circular Error Probability (CEP)



Note. Graphic showing circular error probability (CEP) courtesy of (T. et al., 2006). CEP is essentially a 3-d bell curve. Most of the points occur near the peak or mean of this curve. Where the top 50% of the GPS points occur, that theoretical circle denotes the CEP measurement. When this research refers to the CEP measurements, it is assumed to be an imperfect science based on this theory. This is based on the notion that 50% of the GPS points also fall outside this range.

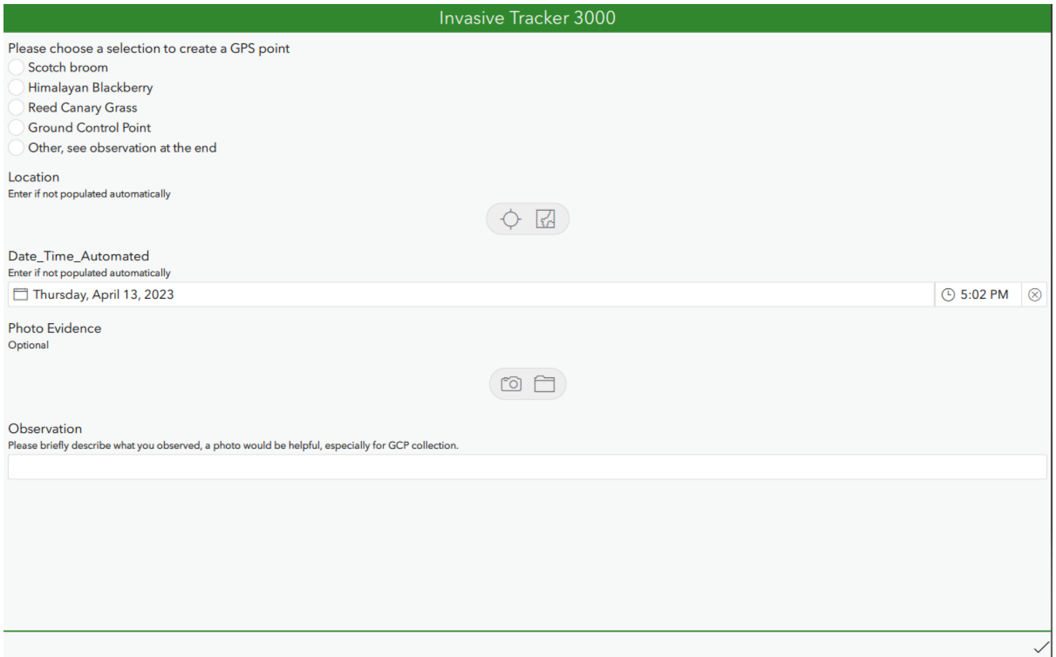
The creation of ground control points (GCP)s for this research incorporated several existing features, such as a bus stop and concrete barriers at the Cooper Crest site. A GCP is a reference location with a known x, y, and z coordinate attached. The Cooper Crest site maintained a series of permanent GCPs created by Evergreen instructor Mike Ruth to increase map precision from 5-10 meters to submeter accuracy. However, several original GCPs were destroyed during the initial runoff/erosion mitigation phases and the industrial mulching that supported those mitigation techniques.

It is important to note that even without the addition of GCPs, the project remains relatively accurate in the 5–10-meter range, which may suffice for a restoration site. Furthermore, even with the loss of the original GCPs, the new orthomosaics created were co-registered with the original orthomosaics. Co-registration involved a previously corrected orthomosaic and transferring its georeferenced information to another orthomosaic along with its elevation model. This method of ortho correction supported EBM and my research goals with streamlined processing and shortened flight missions. This method lies outside the scope of this research; however, there are bountiful workflows available (ESRI Georeference a raster to another raster, n.d.)

GPS Data Collection. With the addition of the Geode device collecting precision locational data, ESRI's Survey123 application was employed for all GPS data collection starting in December 2022 and ending in April 2023. Evergreen instructor Mike Ruth designed the Cooper Crest survey to track several metrics that relied upon accurate GPS locations. This survey proved the utility of precision GPS in ecosystem management and adds value when incorporated into spatial systems. In addition, I used Survey123 to create an additional survey to exhibit ground truthing relating to invasive detection that includes the metrics seen in Figure 12 below.

Figure 12

Invasive Tracker 3000 Survey



Note. This screenshot captures the basic survey schema with location, time, and date completed automated. The location is set only to capture points using the Geode precision GPS unit and easily ties into the ESRI suite of products.

Preparation

Data Preparation and Storage

Data preparation had several stages in this project's development. Storing the data by project, source, or file type greatly assisted with limited hard drive availability. It is generally a given that data sources and formats are also stored in their original form to the greatest extent possible (ESRI, 2018). Data storage for this project primarily took place on a secondary internal HDD and an external HDD. In addition, I stored all project and non-imagery files in an internal SSD that offered nearly twice the processing speed compared to the traditional HDDs. This efficiency was especially noticeable when building orthomosaics in any program and for deep learning processes.

Large projects can have enormous quantities of data associated with them. This project alleviated that by creating multiple smaller projects to conserve system resources. Each project maintained its source data, geodatabase, and relevant layers while simultaneously being exportable for analyses or upload to ArcGIS Online (AGOL). This decision helped speed up initial data management and reduced the resource load on the five-year-old gaming laptop used to process this research's interconnected parts. A recommendation is to ensure that the SSD or HDD has at least 100GB of available memory. These programs will work with less; however, they seem to become relatively unstable as the percentage of free memory is lessened. This is especially true with WebODM and Drone2Map, which influenced the decision to use ArcGIS Pro to the greatest extent possible.

In addition to large quantities of data are the metadata attached to the files. Using the GeoTIFF format in ArcGIS allowed the rapid retrieval of georeferenced information. In addition, ArcGIS creates small attached .aux.XML files to store the metadata, which further supports the use of less powerful computer processors by acting as a quick geotag for the computer to recognize. This bit of user knowledge inadvertently supported EBM by helping minimize the need for additional technology upgrades, such as a GPU with 12GB or more of VRAM or bandwidth increases. This was especially true for shared communications through mediums such as email or limited bandwidth networks, which I discovered my rural location faced.

Orthomosaic Workflows in ArcGIS Pro

Once essential data preparation and storage were complete, the orthomosaic building process took place. Rather than reinventing the wheel, this research incorporated many different workflows designed and tested by the experts at ESRI. While the detailed creation of orthomosaics was outside the scope of this research, I found that the quality of an orthomosaic played the most substantial role in the rest of the project. Therefore, this paper discusses several critical settings used in the ESRI workflows in the methods, results, discussion, and conclusion. During the summer of 2022, ESRI redesigned its drone2map platform with a proprietary algorithm while eliminating the previous Pix4d-powered engine. Unfortunately, this update did not work well with my older laptop, like many first-generation products. Due to these complications, I could not fully exhibit the old method of orthomosaic development, having since updated the program in the late fall of 2022. In addition, this research decided to incorporate a constraint to minimize associated costs by using only ArcGIS Pro to the greatest extent possible.

After each successful and safe flight mission, the sUAS collected imagery was photogrammetrically corrected using the ESRI imagery workflow "Create Drone Imagery Products in ArcGIS Pro" (ESRI, 2022). This workflow contained the following steps:

- Create an ortho-mapping workspace dedicated to a single mission's imagery collection.
- Adjust the tie points or blocks for proper image orientation.
- Import and add ground control points (GCP)s, NOT required, but can provide additional elevation values and precision for projects requiring more accuracy.
- Create a digital surface model showing all the above terrain features inside the spectral band (DSM).
- Create the orthorectified image product from a mosaic of images.

First, creating a project using a projected coordinate system is vital to minimize data distortions. In this case, the EXIF headers from the sUAS had a spatial reference that only allowed for universal transverse Mercator (UTM) zone 10. This was because the DJI vertical coordinate system was preprogrammed for WGS1984 and was not modifiable on my laptop, which was somewhat surprising. For this reason, the specific settings in the tables below may not directly translate to another research, especially when using a brand other than DJI. Second, setting the project PCS first was unnecessary as the ortho mapping wizard will perform that function for the entire project during its processing.

The first tool incorporated was the above ESRI imagery workflow to create the necessary orthomosaic to perform various deep learning operations. The ESRI workflow and guided ortho mapping wizard used the preliminary settings in Table 1 below. It is important to note that with the goal of this research being to limit costs, there was no application of RTK, PPK, or other precision GPS for these settings and products to test these settings with minimal inputs.

Table 1

New Ortho Mapping Workspace Settings

Sensor Data Type	Drone
Allow adjustment reset	Not checked "preserves substantial system resources" does not allow ortho refining
Sensor Type	Generic
Geolocation*	[Loaded from EXIF]
Spatial Reference*	WGS_1984_UTM_Zone_10N / VCS: WGS_1984
Camera Model*	FC6310S (Phantom 4 Pro v2 RGB camera)
Elevation Source	Average Elevation from Image Metadata
*	These items populate after selecting the folder location containing the image set. In addition, ArcGIS Pro automatically adjusts for the geolocation, spatial reference (X, Y, and Z), and camera model using EXIF headers and other system information provided by the sUAS flight recording data. If not available, these selections will all be input manually.

After setting up the ortho mapping workspace, ArcGIS Pro populated a tab on the top of the user interface that says [Ortho Mapping]. The next step in the workflow involved the creation of tie points using the [Adjust > Adjust] and the settings in Table 2. Tie points are used in stereo imaging and represent the same point seen from multiple perspectives. ArcGIS Pro considers each tie point a stereo pair. Maintaining a good balance of these points is necessary to minimize DSM distortions, artifacts, and holes. This directly equates to a higher quality orthomosaic and a better foundation for future use cases, including deep learning applications.

Table 2

Adjust Settings

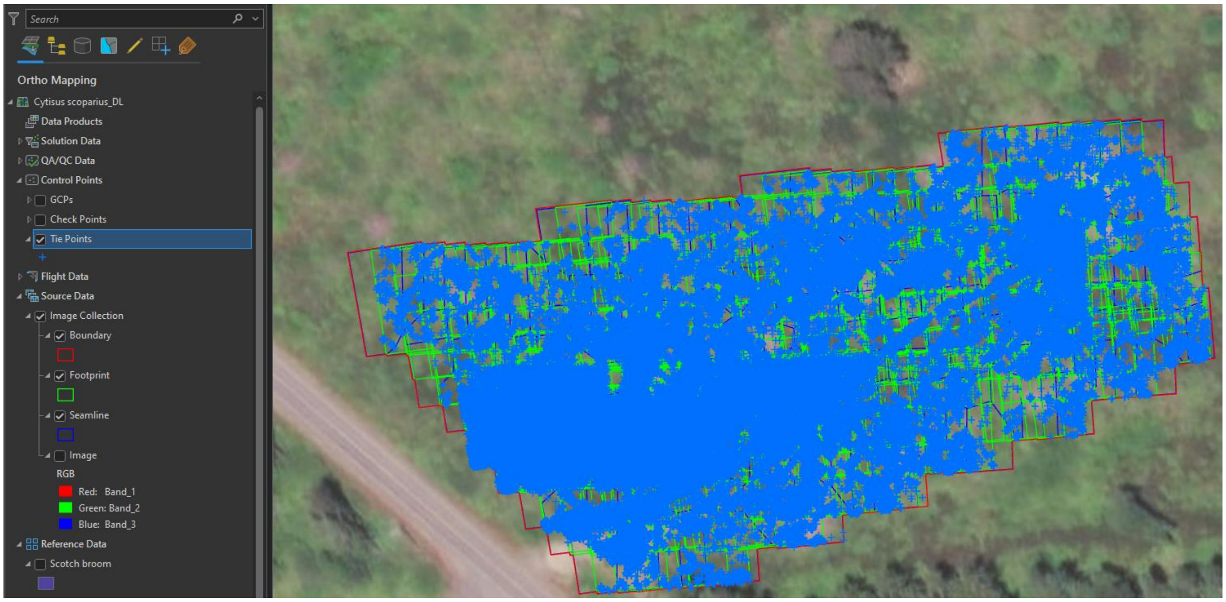
Block Adjustment	Leave empty
Focal Length	Check the box
Principal Point	Check the box
K1, K2, K3	Check the box
P1, P2	Check the box
Fix Image Locations for High Accuracy GPS	Leave empty unless using RTK or PPK
Image Location Accuracy	Medium, unless using RTK or PPK

After [Adjust], the following steps involve the contextual tab [Refine]. This is the step that can incorporate GCPs if necessary and available. While GCPs are unnecessary, they add tremendous value, as noted prior. Under [Adjust], there are tabs to [Manage Tie Points] and [Manage GCPs]. Again, as this project sought to reduce costs and simulate no terrestrial access, GCPs were not implemented. However, if GCPs were required, an applicable survey using Survey123, or another compatible collection method may be imported directly into Pro using the ESRI imagery workflow "Create Drone Imagery Products in ArcGIS Pro" (ESRI, 2022).

Within [Manage Tie Points], there were options to edit, analyze, and recompute, which may be necessary depending on the image overlap, time of day, season, angle of the sun, and a variety of other mapping-related distortions. For example, Figure 13, below, shows the 273,791 tie points as blue pluses overlaid on the image collection consisting of the project boundary, image footprints, and seamlines. After an additional recompute and verification, the tie point quantity was significantly increased to 454,301, as seen in Figure 14 below.

Figure 13

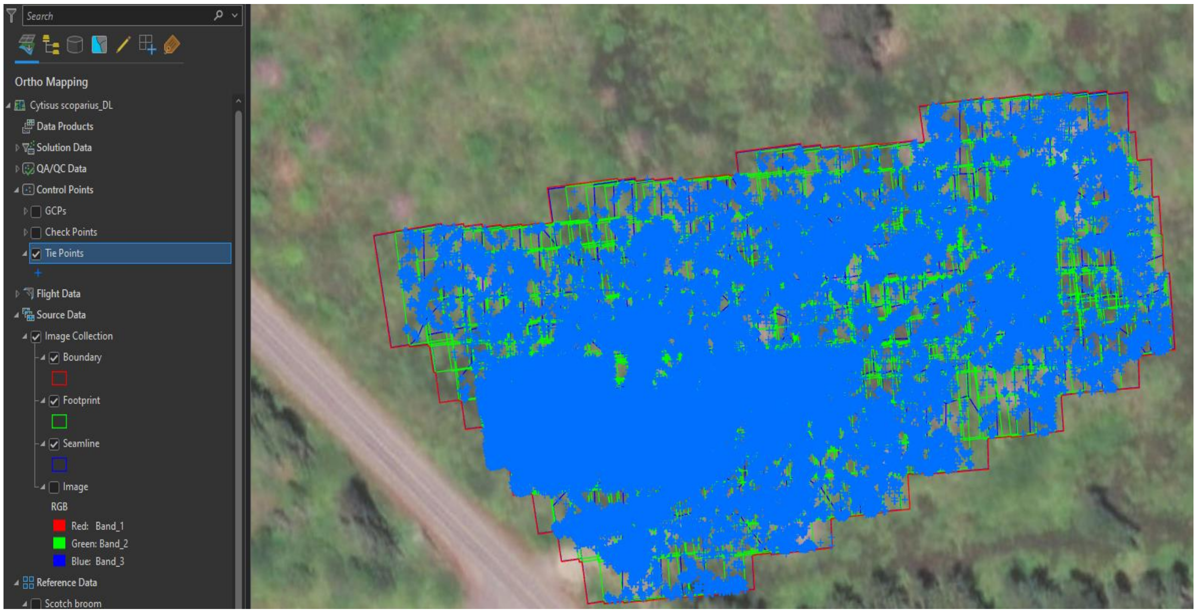
Image Collection and Tie Points Before Final Recompute



Note. This figure shows the contents tab with the image collection layers overlaid by 273,791 tie points. There are gaps in the tie points that stem from the sun's low angle, which causes long shadows and several types of distortion. ArcGIS Pro allows editing, recomputing, and additional analysis to close these gaps. This image was edited multiple times and recomputed four times to get to this quality.

Figure 14

Image Collection and Tie Points After Final Recompute



Note. This figure shows the recomputed tie points after one additional recompute (14 mins) and a manual edit. The tie point quantity increased to 454,301 from 273,791 stereo pairs.

After modifying tie points to their most significant potential, creating a digital elevation model (DEM) followed using the 454,301 recomputed tie points. An important note is that when adjusting tie points, the [Adjust] tool must be run before the elevation model starts. Under [Products], the option to create a DSM or DTM will be contextually highlighted. A digital surface model (DSM) is an elevation model showing the height of all-natural and human-made structures. A digital terrain model (DTM) captures the surface elevation of the Earth without structures or natural features. Choosing between the two depends entirely on the site. In this instance, vegetation density made the DSM a better option as a reliable DTM was improbable to capture the values needed.

After selecting [DSM], this project used all the default settings within the point cloud and DSM settings. The most important setting to determine before running the [DSM] tool was the [Matching Method] on the second page of the tool. Semiglobal, extended terrain, and Multiview matching are three approaches used in computer vision and photogrammetry to perform dense image matching for 3D reconstruction.

Semiglobal Matching (SGM): SGM is a popular approach for stereo matching, which involves finding corresponding points between two or more images taken from different viewpoints. SGM takes a cost-volume-based process, where for each pixel in the reference image, a matching cost is computed for all possible pixels in the other image(s). The price is then aggregated over a path along the image grid to obtain the optimal disparity value. SGM is known for its accuracy and efficiency and is widely used in applications such as autonomous vehicles, robotics, and augmented reality.

Extended Terrain Matching (ETM): ETM is a refinement of SGM that considers the scene's terrain relief and other geometric properties. ETM introduces a regularization term that enforces smoothness and continuity constraints on the disparity map, which helps to reduce the effects of noise and occlusions. ETM is particularly useful in complex and rugged terrain applications, such as mountainous regions or urban areas with high-rise buildings.

Multiview Matching (MVM): MVM is a technique that combines data from multiple images of the same scene taken from different viewpoints. MVM can obtain a more complete and accurate 3D representation of the scene by fusing the information from different perspectives. MVM involves finding correspondence between all pairs of images and then computing the 3D position of each point in the background using triangulation. MVM is commonly used in aerial and satellite photogrammetry, cultural heritage preservation, and urban planning applications.

Given the database site’s relative flatness, lack of powerful features, and little need for 3d modeling, semiglobal matching (the default setting) was deemed the best tool to create a quality DSM. Following the creation of an elevation model, DSM, in this case, comes the next step of orthomosaic design.

In the [Ortho Mapping] tab, under [Product] is the [Orthomosaic] contextual tab. This step incorporated all the default settings with a few exceptions. Depending on a site's needs, the elevation source should be selected. This research included the DSM to provide elevation services, as noted prior.

After attempting each computation method offered in the ortho mapping wizard, the Voronoi method was deemed the most effective at reducing seasonal issues and distortions by comparing the products individually. The Voronoi computation method is used in deep learning for object detection and segmentation. It involves dividing the input image into multiple cells or regions based on the nearest neighbor algorithm and assigning each image pixel to the cell containing its nearest neighbor. The Voronoi diagram is a mathematical concept that defines cell boundaries based on the distance between their nearest neighbors. In deep learning, this concept is applied to partition the input image into cells or regions, and each cell is assigned a label or category based on the objects or features it contains.

This method has been used in various deep-learning applications, such as image segmentation, object detection, and instance segmentation. The Voronoi computation method can improve the accuracy and speed of these tasks by reducing the amount of computation needed to process the critical image with limited system resources. Overall, the Voronoi computation method is a valuable technique for deep learning applications that involve object detection and segmentation, and it has the potential to be applied in a wide range of other tasks as well.

The last page of the [Ortho Mapping Products Wizard] involves the pixel size, format, and compression for the orthomosaic. This research used this page's default settings to create the best orthomosaic. Running this tool took approximately 30 minutes using the default settings and generated the orthomosaic seen in Figure 15 below.

Additionally, one can notice the long tree shadows stretching along the edges of the orthomosaic from the sun's low angle at noon in February. At a more detailed level, the low sun angle caused distortions and artifacts that were not easily remedied, making the model substantially less effective. However, even with these distortions and artifacts, the number of potential samples totaled in the thousands. These distortions are described more in-depth within the results and discussion sections.

Figure 15

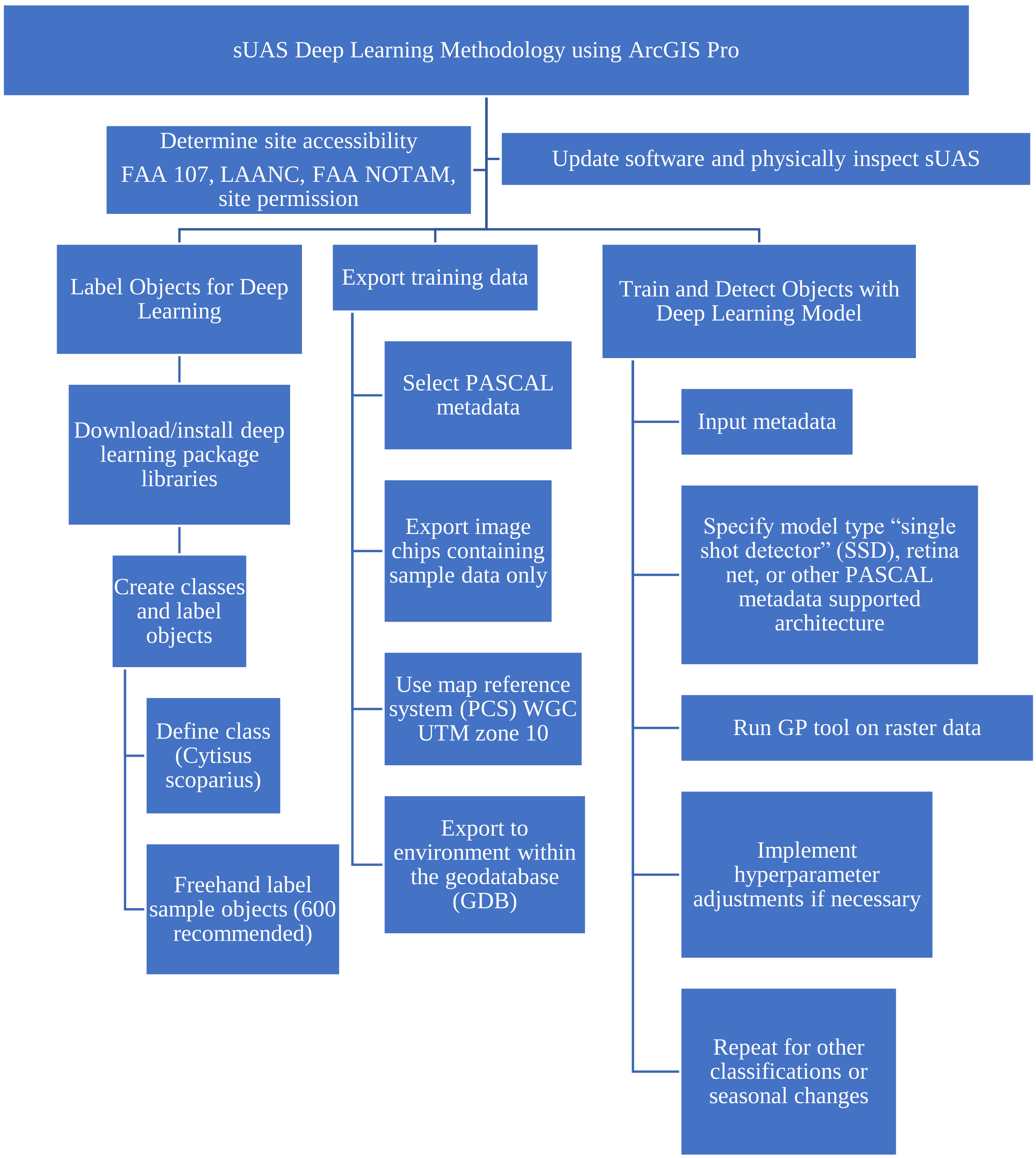
Scotch Broom Orthomosaic

Note. This figure shows the recomputed tie points after one additional recompute (14 mins) and a manual edit. The tie point quantity increased to 454,301 from 273,791 stereo pairs.

Deep Learning Model

Figure 16

Deep Learning Model Conceptual Model



Note. Conceptual model of deep learning workflow methodology.

A deep learning model was incorporated using an artificial neural network architecture in Python using installed TensorFlow and Keras libraries. ESRI Indonesia initially designed and built this model for the agricultural industry, primarily palm oil. Since its inception, ESRI has invested heavily in deep spatial learning, which further supports this innovative EBM technique. An overwhelming majority of instances are in mono-crop agriculture, in which ESRI models maintain 95% accuracy in CEP and recognition. This model was trained using the Scotch broom images acquired from February-April 2023 during the sUAS flying off-season. It is important to note that object detection and object classification are slightly different tools. This model focuses on recognizing a particular species with aerial imagery, precisely its location. Based on these requirements and the high resolution of sUAS imagery, object detection was deemed the proper choice for EBM applications on this smaller scale. For large projects, object classification is a recommended setting to investigate. However, it is outside the scope of this research.

This deep-learning GIS model was trained using ArcGIS Pro. The choice of deep learning model and software tools depends on the data's characteristics and the research goals. Overall, deep learning models in GIS represent a powerful tool for analyzing and interpreting large and complex geospatial data sets. This deep learning model provided valuable insights and supported informed decision-making in EBM by automatically learning patterns and relationships in labeled data.

With the completed Scotch broom orthomosaic selected in the contents pane, I implemented the classification tool for labeling objects in deep learning. ESRI recommends having around 600 individual samples, “this project had 607”, with the first sample seen in Figure 17 below (Abdilah, 2021). It took about three hours to create the schema and label the Scotch broom within the training orthomosaic. The orthomosaic seen in Figure 18 below shows the extent of the training samples from a perspective of 1:677.

Figure 17

Cytisus Scoparius Sampling

Note. This figure shows the first of approximately 600 samples taken to train the deep-learning model to recognize Cytisus scoparius. The stump directly to the left of the encircled plant shows minor visual distortions from the low sun angle. To the right, the long shadows are also prevalent; note that this imagery was taken around noon in mid-February.

With the orthomosaic layer selected in the contents pane, select [Imagery]. Under the [Image Classification] > [Classification Tools] tab, this research incorporated the [Label Objects for Deep Learning] tool. Figure 17 above shows the image classification tool used to generate the schema, label the objects, and export the training data. This figure also shows the first manual drawn selection used to create the model. As this research only sought to identify Scotch broom, a single class with one value was created for the schema and subsequently labeled using the freehand tool, further detailed in the workflow [Label Objects for Deep Learning] (ESRI, 2022).

A special note regarding this setting is that when saving the labeled objects, ensure that they are saved within the geodatabase folder within the project's storage location. Not doing so will result in the future steps being unable to access the labeled data and will require a complete redo of the labeling steps and several hours. On the other hand, this will save many hours of troubleshooting and was a standard issue during the initial testing stages of this research.

After labeling the Scotch broom, selecting the export training data to the right of the labeled objects gave various options. The TIFF format and PASCAL Visual Object Classes metadata supported this research's deep learning model architecture. In addition, the TIFF format can be compressed, which helps reduce the data load on the SSD.

When a GeoTIFF file is created, it can be compressed using various methods such as LZW (Lempel-Ziv-Welch), DEFLATE, or JPEG. These compression methods can reduce the file size and make it more manageable for storage and transfer, which was necessary with the system's limited storage capacity. However, compression can also result in a loss of quality, depending on the type and level of compression used. Therefore, choosing the appropriate compression method and level is essential to balance the file size and quality needs.

The PASCAL Visual Object Classes (VOC) is a popular benchmark dataset for computer vision object detection, recognition, and segmentation tasks. The dataset consisted of a set of mosaicked images and 607 annotations that specified the locations and categories of identified objects within the images. The dataset is commonly used for evaluating and comparing the performance of different object detection and recognition algorithms. It includes a standard set of evaluation metrics, such as mean average precision (mAP), allowing researchers to compare their algorithms. This was essential, as the model was developed using non-site access, and some measure of effectiveness was crucial.

In addition to the primary PASCAL VOC dataset, there are several related datasets, including the PASCAL Context dataset, which includes annotations for object segmentation and scene understanding, and the PASCAL-Part dataset, which contains annotations for object parts. PASCAL was also chosen because it was more functional, given the lower system resources that constrained this research.

Figure 18

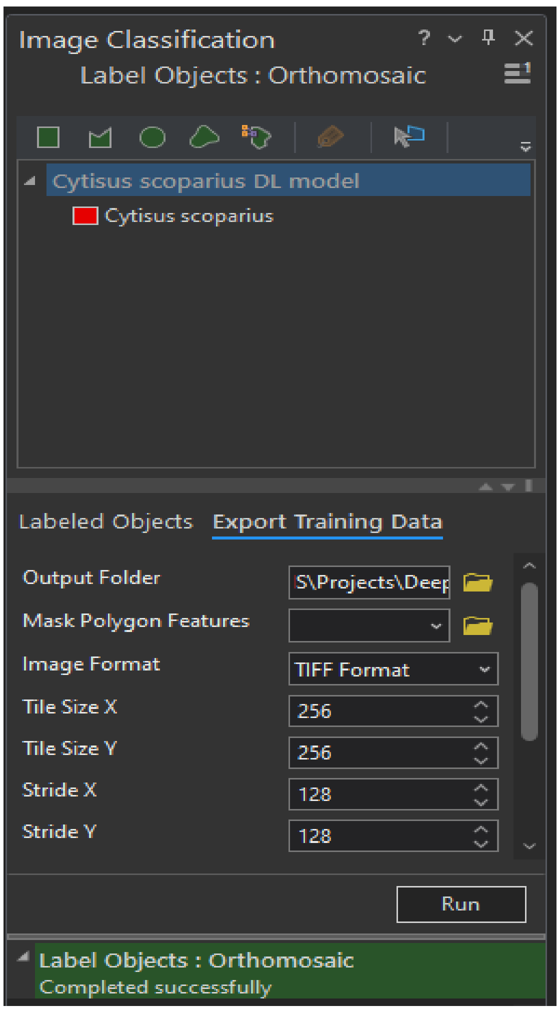
Labeled Cytisus scoparius Samples for Deep Learning

Note. This is the same orthomosaic as the previous figure. However, this highlights all the 607 labeled Cytisus scoparius samples used to train and run the deep learning model.

Deep learning models within the ESRI suite can range from complex to rather basic. For example, this object detection model used only Scotch broom as a variable in complexity. The schema supporting this was named *Cytisus scoparius* DL model and used a single classification manually outlined in red (see Figures 17 and 18, above). After the schema and classification labels were completed, it took 4 minutes and 48 seconds to export the training data to a file storage location for further training (see Figure 19 below).

Figure 19

Image Classification

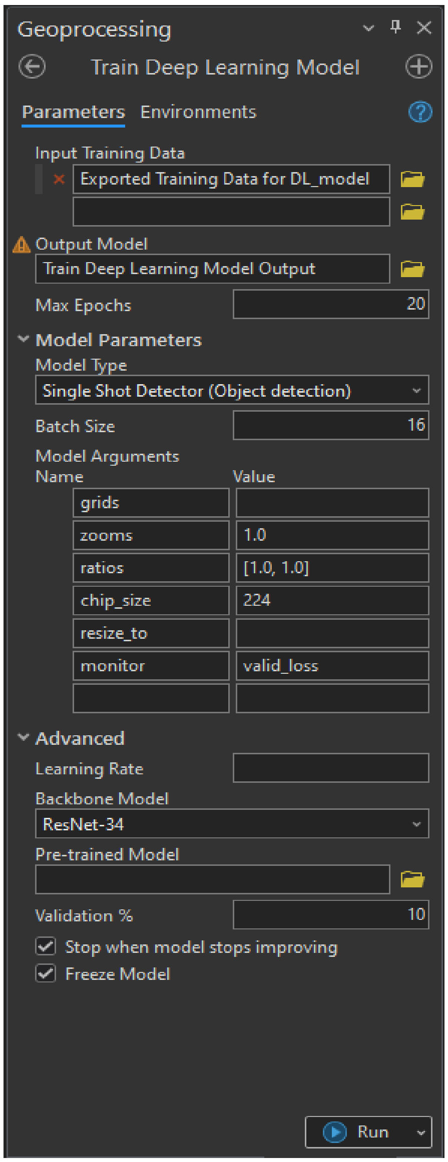


Note. This figure captures the schema, classification, and output information in the "Label Objects for Deep Learning" tool. After this step, the training data is exported, which can be used to train a deep learning model.

Following the labeling and exporting steps, the next is to train the deep learning model. The following parameters were set to train the model (See Figure 20 below). To train the model, all the products up to this point are used to support the [Train Deep Learning Model] geoprocessing tool. This tool was accessed through the [Analysis] > [Tools] > [Train Deep Learning Model].

Figure 20

Train Deep Learning Model



Note. This figure captures the schema, classification, and output information in the "Label Objects for Deep Learning" tool. After this step, the training data is exported, which can be used to train a deep learning model.

After selecting the run, the model will begin training based on the desired parameters. It took 37 minutes and 20 seconds for my computer to train these parameters using batch processing of less than 16. Anything above 16 would cause a memory error based on the system specifications; refer to Figure 20 above for the batch size setting. This is because the batches process as squares in forward and backward directions, and the limited VRAM could not effectively run the model at greater loads. In fact, the model often ran out of memory at any higher settings which is a processing power specific issue.

Model Evaluation

As discussed more thoroughly in the results and discussions section, I attempted to evaluate the model's performance utilizing various metrics such as precision, recall, and F1 score. Precision and recall are two crucial measures of model performance for binary classification problems, and the F1 score provides a single value that summarizes both precision and recall. These metrics are essential to comprehensively evaluate the model's ability to identify positive instances accurately and attempt to make meaningful comparisons between different models or configurations (Qian et al., 2020). Unfortunately, lacking local processing power limited the available deep-learning package options for developing and building the model. These evaluation methods could become more critical in the later stages of EBM when designing a comprehensive multi-species identification model for an entire ecosystem which would likely require greater processing power and hence a more powerful computer.

Precision is a measure of the accuracy of positive predictions made by the model. It is the ratio of accurate positive predictions (correctly classified positive instances) to the sum of accurate positive and false positive predictions (incorrectly classified negative instances as positive). High precision would indicate the model had low false positive rates, making few incorrect positive predictions.

Recall is a measure of the ability of the model to detect all positive instances. It is the ratio of accurate positive predictions (correctly classified positive instances) to the sum of accurate positive and false negative predictions (incorrectly classified positive instances as negative). For example, a high recall would indicate the model had low false negative rates, meaning it correctly identified most positive instances.

The F1 score is the harmonic mean of precision and recall. The F1 score provided a single value to summarize the model's performance. It is defined as 2 * (precision * recall) / (precision + recall). The F1 score accounted for both precision and recall, making it a valuable metric for evaluating the model's overall performance when the cost of false positive and false negative predictions was the same.

These three metrics are a potential output of ESRI's ArcGIS Pro when creating a deep learning model. The evaluation results will be presented in the results and discussion sections. Unfortunately, achieving some of these output metrics was not feasible due to the natural and simulated constraints placed on this research, however, the precision score is available and shows the potential of the model, even with the heavy limitations.

Model Deployment

The trained model was then deployed in ArcGIS Pro using the ArcGIS API for Python. The model was used to classify additional Scotch broom samples and map the distribution of Scotch brooms in the site area. This model was predeveloped by ESRI, which eliminated most of the steps required to develop effective deployments. These prebuilt steps included packaging the model, deploying the model into the cloud or software, model scaling, and securing the model.

Detecting objects was conducted using the [Analysis] tab > [Tools] > [Detect Objects Using Deep Learning]. With this tool open, I selected the raster input or orthomosaic layer, created an output location, and selected the .dlpk or deep learning package. This process ran for several minutes, resulting in a large detection dataset that can offer insight into refinement, monitoring, and updating for future use case scenarios. The results of this processing can be found in the results and discussion section.

The remaining steps that this research incorporated were monitoring and updating. Monitoring in this context referred to the real-time analysis of Scotch broom data, correct identification of Scotch broom, and addressing any issues on-the-fly. Furthermore, ESRI supports all these packages, which are both free for download and valuable for people with zero coding background as the processes run within the software as inputs rather than code if desired.

Updating the model was another step for the continued successful deployment of this model. Updating periodically helped improve initial accuracy; however, this project's scope did not require extensive updating outside of adding more recognition examples for a better identification ratio. For example, a proof-of-concept model was designed and ran successfully. The initial model had a 31% identification rate in the sample database with only 67 samples. The final model expanded upon this quantity nearly tenfold to 607 pieces.

In the future, training the model to identify Scotch broom in the reproductive stage could be considered a form of updating; however, the original classification schema would consider it a new object to classify as the spectral bands are substantially different. For example, the Scotch broom was in a dormant winter stage in the training dataset. While the Scotch broom stuck out during the winter because of its status as an evergreen plant, the model would likely not recognize the signature bright yellow flowers of the Scotch broom. Had this project lasted several years, having training datasets to identify dormant and reproductive plants correctly would be beneficial and further improve EBM. Additionally, using RGB sensors to save costs would limit the effectiveness compared to a multispectral sensor capable of singling out the vegetation and delineating the yellow bands with tremendous success.

Validation

The model's results were validated using manual observations in the ArcGIS Pro application. Validation was essential in developing this deep learning model. Validation assessed the model's performance and accuracy in recognizing the objects of interest. The validation process involved comparing the model's classification results with the ground truth information obtained from field observations and manual annotations. This meant visually inspecting the model's classifications and comparing them to the presence or absence of invasive species in the study area.

In the context of recognizing Scotch broom, the validation of the model's classification results was carried out using the following method:

- Visual Inspection: The model's classifications were inspected by comparing the model's predictions to high-resolution aerial or satellite imagery of the study area. This concerned visually inspecting the model's classifications and comparing them to the actual presence or absence of Scotch broom in the study area using manual spatial identification given the lack of ground truthing.

Additionally, a study or database using ground control and ground truthing might implement a Confusion Matrix Analysis (CMA). A confusion matrix analysis, also known as an error matrix, is a technique used to evaluate the performance of a classification model, including those built with deep learning algorithms. It provides a summary of the predictions made by the model compared to the actual ground truth labels.

The confusion matrix is typically represented as a square matrix, where the rows correspond to the actual class labels and the columns correspond to the predicted class labels. The diagonal elements of the matrix represent the number of correct predictions (true positives and true negatives), while the off-diagonal elements represent the number of incorrect predictions (false positives and false negatives).

Here is an example of a confusion matrix:

Table 3

Confusion Matrix

	Predicted Negative	Predicted Positive
Actual Negative	TN	FP
Actual Positive	FN	TP

TN: True Negatives (correctly predicted negatives)

FP: False Positives (incorrectly predicted positives)

FN: False Negatives (incorrectly predicted negatives)

TP: True Positives (correctly predicted positives)

The confusion matrix provides insights into the model's performance by showing the distribution of correct and incorrect predictions across different classes. From the matrix, various evaluation metrics can be derived, such as accuracy, precision, recall (sensitivity), specificity, and F1 score, which help assess the model's effectiveness in classifying different categories.

By analyzing the confusion matrix, patterns and trends in misclassifications can be identified, allowing for adjustments in model training or addressing specific challenges related to certain classes. This analysis aids in understanding the strengths and weaknesses of the deep learning model and assists in making informed decisions to improve its performance.

Overall, the confusion matrix analysis is a valuable tool in evaluating the classification performance of deep learning models, enabling a deeper understanding of the model's predictive capabilities, and guiding further optimization and fine-tuning processes.

Model Refinement and Interpretation

Deep learning models in ArcGIS Pro are typically used to extract information from large and complex spatial datasets, such as satellite images, aerial photographs, or LIDAR data. These models are built using advanced neural network architectures, which are trained on labeled data to learn patterns and relationships that can be used to make predictions or classify new data.

However, even the best deep-learning models can produce inaccurate or unreliable results if they are not adequately refined and interpreted. Here are some reasons why model refinement and interpretation are essential in GIS:

Performance optimization: Model refinement is fine-tuning the deep learning model to improve its accuracy, speed, and generalizability. This involves selecting the appropriate hyperparameters, adjusting the architecture, and optimizing the training process to minimize overfitting or underfitting. This step was found to require an extensive amount of coding experience as the parameters are outlined in Python and had a high skill threshold.

Quality control: Model interpretation is understanding how the deep learning model works and what features it relies on to make predictions. This involves analyzing the model's internal representation, feature importance, and decision boundaries to ensure that it is making sensible and consistent predictions.

Explainability: Model interpretation is also essential for providing explanations or justifications for the model's predictions, which is critical for applications such as land use planning, natural resource management, or disaster response. By understanding how the model works, users can better trust and validate its output and communicate its findings to stakeholders.

Model refinement and interpretation are essential for developing accurate, reliable, transparent deep-learning models in ArcGIS Pro. The validation results were then used to refine the model by adjusting its parameters or architecture. The proof-of-concept model previously developed consisted of approximately 60 samples. This model had a significantly lower precision and required more pieces. Following the recommendations, this research incorporated 607 samples to increase this metric. This was done to identify the invasive species more thoroughly in the study area and provide meaningful results for interpretation and discussion in the remaining sections.

5. Results

Overview of Objectives and Methods

This research used a stock DJI Phantom 4 Pro V2.0 to acquire aerial nadir RGB imagery over several locations in western Washington from August 2022 to May 2023. The site locations comprised the *Cytisus scoparius* (Scotch broom) deep learning database sampling and the Cooper Crest Ecosystem Restoration sites. To avoid confusion, these sections focus primarily on the deep learning site location. However, the same or similar methods were applied to the Cooper Crest site until the deep learning training. The sUAS-acquired imagery gathered at these locations was processed using WebODM, ArcGIS Pro, and Drone2map programs, including the authoritative ESRI-supported geoprocessing and product development workflows. The intermediate products created using these programs included adjustment tie points, LAS mesh, and elevation models. Ultimately, these products supported the creation of orthomosaics and the deep learning sampling and training schema (classification, labeling, training, object identification). It is essential also to note here that the deep learning training data can be packaged and utilized across orthomosaics in multiple organizations, making this tool not only replicable but also adjustable and quickly passed along to other organizations running the ESRI software.

This research aimed to determine if using publicly available and affordable sUAS technology and deep learning object detection could innovate EBM, specifically in terms of cost and time, which are often the most impactful variables in long-term environmental management. The chief goals were to create the products needed in the software to correctly classify, train, and identify *Cytisus scoparius*, an invasive species, at a training site. Given that this technology is in its infancy, the results and discussion section aim to examine some of these nuances and how they may affect EBM.

The remaining sections discuss the real-world results of using sUAS-acquired imagery, followed by a discussion of feasibility and thoughts regarding the constraints impacts to developing and using a deep learning model. Ultimately, this research is exploratory and seeks to determine if this type of data acquisition and deep learning object detection is possible during the winter months, given the known constraints and how they may be applied to EBM moving forward.

Intermediate Products

The results of the intermediate products are rather significant because they help build the foundation for orthomosaic development, which supports the deep learning model. The new ortho mapping workspace tool in ArcGIS Pro aligned the approximately 300 images taken at the deep learning site. The new ortho mapping workspace tool incorporated the settings in the methods subsection “orthomosaic workflows in ArcGIS Pro.” It produced the image collection boundaries and overlap seen in Figure 21 below. Additionally, after testing several settings, the medium location accuracy selection in the adjust tab helped develop the best orthomosaic foundation with the combination of the tools and equipment used in this research and the constraints.

Figure 21

New Ortho Mapping Workspace Settings

Note. This image shows the results of the ortho-mapping workspace and adjust settings. The red line is the border of the entire image collection, while the green indicates the borders of each of the 301 separate images acquired for this research.

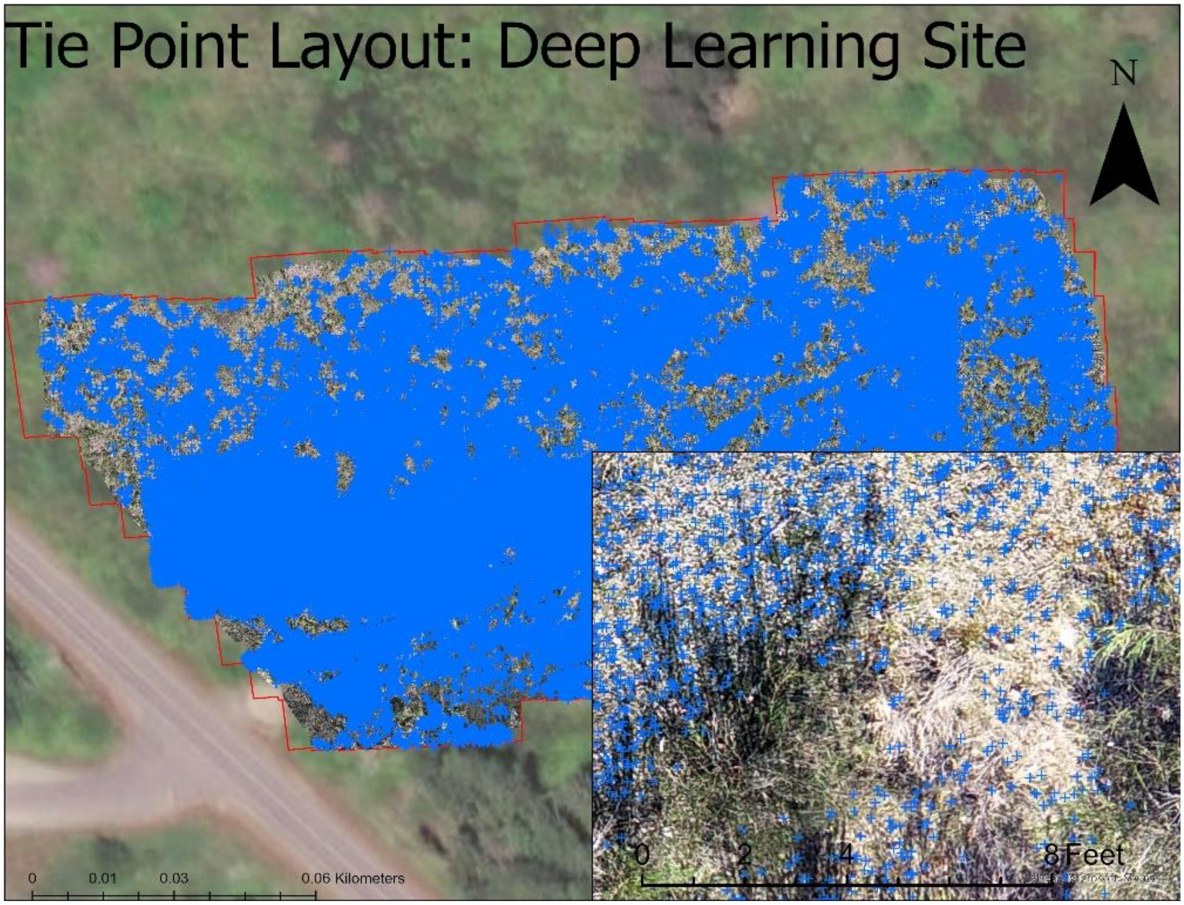
Tie Points

After running the adjust tool in the ortho mapping wizard, the ArcGIS Pro tool generated 273,791 tie points. These points are common locations seen in multiple images used to orient the photos in the collection. Essentially, tie points are generated in pairs across two images, but sometimes more to help combine the images into a geographically accurate orthomosaic. Ensuring that the tie points look good is vital in ensuring a quality orthomosaic is created in a later step. This means minimizing the holes in tie points around the imagery. While this imagery had several such locations, it was not unexpected given the angle of the sun and the long and rapidly changing shadows visibly impacting the orthomosaics.

An important note is that after running the adjusted workflow, the next step may be incorporating ground control points (GCPs) or generating an elevation model. Again, in the spirit of conducting this research with minimal costs and hence equipment, I chose not to utilize GCPs for this site. However, for locations that require rigorous or temporal studies, GCPs are highly recommended as they help to geolocate with much greater precision. Figure 22, below, shows the tie points and a zoomed-in area to show some of the individual points. Additionally, the exact figure shows the solar zenith angle impact on the images in the form of long shadows. The inset on the figure indicates that the program used some of the shadows as tie points to create the DSM and orthomosaic. The issue with this is that as the mission timer continues moving, so do the shadows in the individual images. Once these images are tied together, the slightly changed shadows create artifacts and stretching that would typically not be seen during the summer, when flying missions is ideal.

Figure 22

Tie Point Results



Note. This imagery shows the 273,791 tie points generated to geometrically align the image collection. These tie points help derive an elevation model and support the creation of an orthomosaic with relatively accurate geographic features.

Elevation Models

The next intermediate product was the elevation model seen in Figure 23, below. ArcGIS Pro struggles when creating DSM from drone imagery. Looking at the DSM below, the elevation seems to trend upward, as noted by the increasing yellow and red hues. However, this is not correct when looking at the topographic maps. I was able to troubleshoot this issue by using a different program called WebODM, an open-source application programming interface (API).

However, there were also tradeoffs when not incorporating GCPs into that program, specifically regarding the mean elevation. These are discussed and compared more in-depth in the discussion section.

Figure 23

Digital Surface Model

Note. This image shows the digital surface model (DSM) created in ArcGIS Pro. Unfortunately, the solution points made during the DSM setup show the elevation going higher in a northerly direction, which is invalid. I will address this further in the discussion section regarding challenges faced during the research.

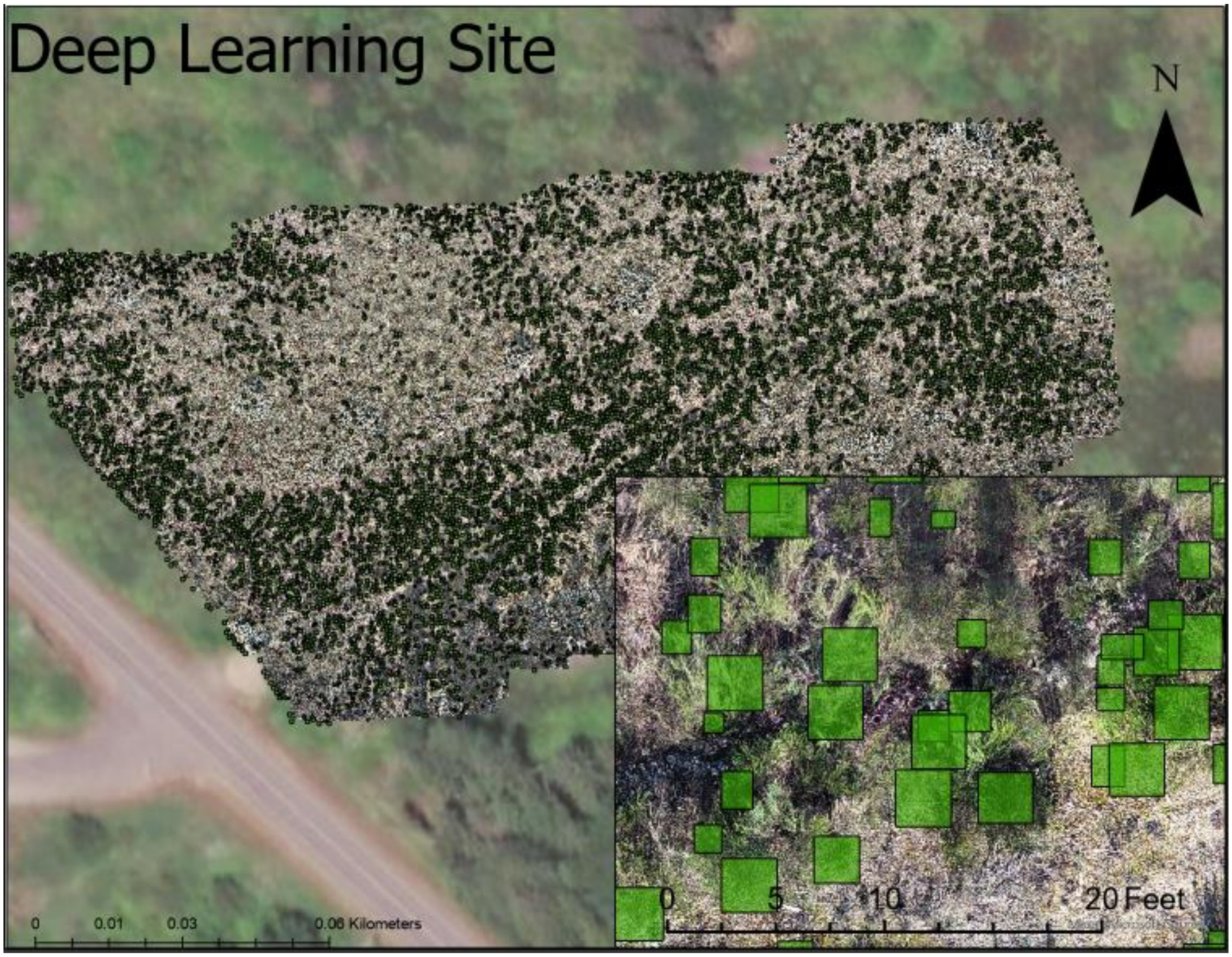
Orthomosaic

The result of the previous steps created an orthomosaic with minimal geometric distortion and balanced colors. The orthomosaic in Figure 24 below took around 45 hours of setting adjustments, and many failed attempts to minimize artifacts, holes, and missing tie point locations. Given the constraints of the solar zenith angle and time of year, the ESRI orthomosaic only accomplished a 5 cm GSD, not quite the goal 1-2 cm GSD wanted. However, it was still high resolution enough to train the model to a respectable accuracy.

Deep Learning Model

Figure 24

Cytisus scoparius Deep Learning Orthomosaic



Note. This figure shows the deep learning database site with the results of the deep learning package using a Single Shot Detector with a model backbone of ResNet-34. The model has around 50% accuracy, which is very low; however, given the constraints of the site, including time of the year, absence of GPS, and weather, the model was a relative success being about 60% more accurate than hypothesized.

Preliminary results for the proof of concept showed an average precision score of approximately .31 or 31%. This is considered extremely low as there is a 69% chance of missing an object detection or falsely identifying a positive. Machine learning typically requires a minimum score of 50-60% to be considered useful to any degree, with anything over 80% regarded as excellent quality. With minor modifications, this result increased to nearly 50% in the proof of concept seen in Figure 24, above. Usefulness is largely context dependent. If a study required centimeter level accuracy and equally high accuracy 80 or 90% might be better suited. However, the results shown in Figure 24, above, and Table 4, and Figure 25 below, show the most recent parameter modification using the ResNet-34 and Single Shot Detector (default settings). The slightly modified default settings performed nearly 60% better than all the other deep learning tool object detection parameters tested for this project and indicates potential for EBM applications that do not need 100% accuracy or precision.

Table 4

PyTorch Lines of Code

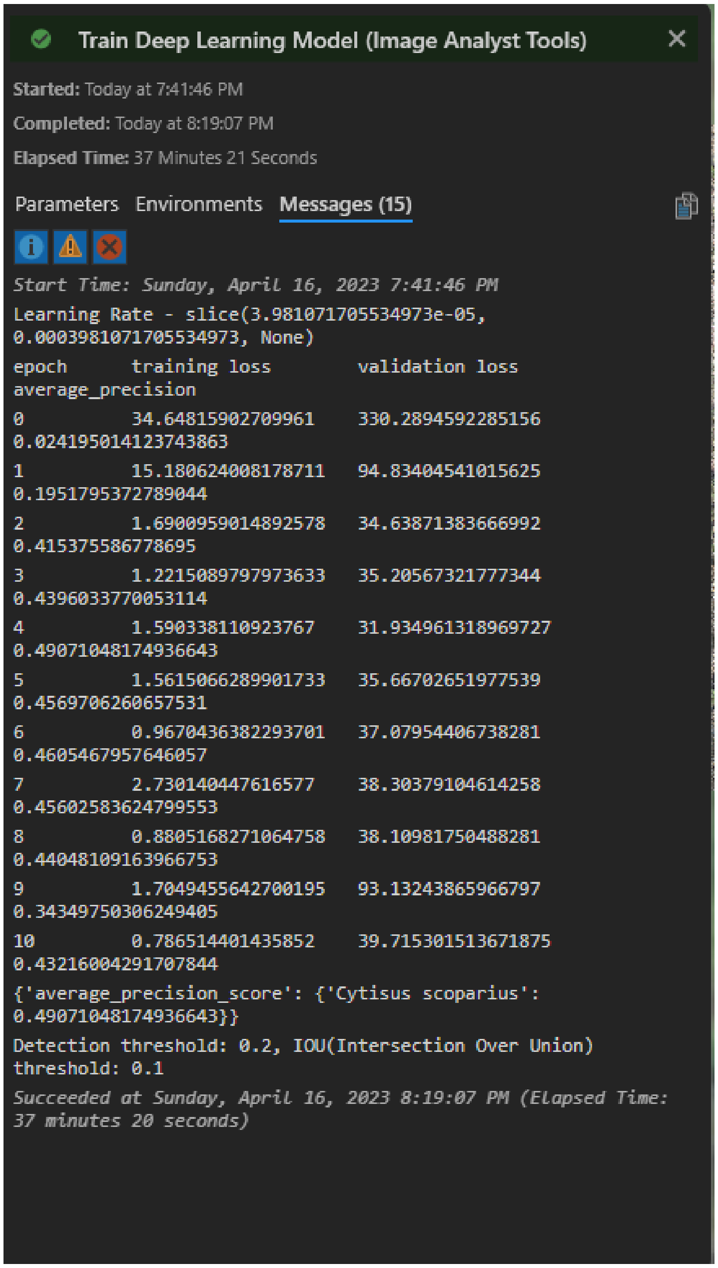

```
{
    "Framework": "arcgis.learn.models._inferencing",
    "InferenceFunction":
"[Functions]System\\DeepLearning\\ArcGISLearn\\ArcGISObjectDetector.py",
    "ModelConfiguration": "_DynamicSSD",
    "ModelType": "ObjectDetection",
    "ExtractBands": [
        0,
        1,
        2
    ],
    "backbone": "resnet34",
    "Grids": [
        1,
        2,
        7
    ],
    "Zooms": [
        1.0
    ],
    "Ratios": [
        [
            1.0,
            1.0
        ]
    ],
    "SSDVersion": 2,
```

```
"Classes": [
  {
    "Value": 1,
    "Name": "Cytisus scoparius",
    "Color": [
      38,
      182,
      63
    ]
  }
],
"ModelFormat": "NCHW",
"MinCellSize": {
  "x": 0.003599999999991883,
  "y": 0.0035999999999910045,
  "spatialReference": {
    "wkid": 32610,
    "latestWkid": 32610,
    "vcsWkid": 115700,
    "latestVcsWkid": 115700
  }
},
"MaxCellSize": {
  "x": 0.003599999999991883,
  "y": 0.0035999999999910045,
  "spatialReference": {
    "wkid": 32610,
    "latestWkid": 32610,
    "vcsWkid": 115700,
    "latestVcsWkid": 115700
  }
},
"SupportsVariableTileSize": false,
"ArcGISLearnVersion": "2.1.0.2",
"monitored_valid_loss": 31.934961318969727,
"ModelFile": "Train Deep Learning Model Output SingleShotDetector and ResNet34.pth",
"ImageHeight": 224,
"ImageWidth": 224,
"ImageSpaceUsed": "MAP_SPACE",
"LearningRate": "slice('3.9811e-05', '3.9811e-04', None)",
"ModelName": "SingleShotDetector",
"backend": "pytorch",
"ModelParameters": {
  "backbone": "resnet34",
  "backend": "pytorch"
},
```

```
    "average_precision_score": {
        "Cytisus scoparius": 0.49071048174936643
    },
    "resize_to": null,
    "IsMultispectral": false
}
```
Note. This table shows the specific lines of code and tools used to generate the model parameters in the emd or JSON file extension type. This code is written in Pytorch or Python and shows the learning rate, tools, and, more importantly, the average precision score of the most recent model.

Figure 25

Results of Train Deep Learning Model Tool



Note. This figure shows the first 10 of 20 epochs. The deep learning model used the default settings of ResNet-34 for the backbone and Single Shot Detector (SSD) as the model. These modified default settings resulted in an approximately 61% increase for a precision score of 0.49. While still considered extremely low, this model is improving and shows excellent promise viewing the time of year, the angle of the sun, and reliance on off-season weather patterns.

Assessing Model Accuracy

A precision score of 49% in a spatial deep learning model for Scotch broom detection indicates that the model correctly identified Scotch broom instances 49% of the time among the predicted positive cases. The precision score measures the accuracy of positive predictions made by the model.

A precision score of 49% suggests that the model is prone to a relatively high number of false positives. It means that roughly half of the instances identified as Scotch broom by the model may be incorrect. This can have significant implications for Scotch broom management and decision-making.

In terms of Scotch broom control efforts, a low precision score means that resources may be wasted on targeting areas that are falsely identified as having Scotch broom presence. This can lead to inefficient allocation of resources and potentially overlook areas where Scotch broom is genuinely present. It may result in ineffective management strategies and a failure to address Scotch broom infestations properly.

Furthermore, the reliability and credibility of the model may be questioned due to its low precision. Stakeholders and policymakers may be hesitant to rely on the model's outputs for decision-making if there is a high likelihood of false positive identifications. This can undermine trust in the model's predictions and hinder its adoption in practical applications.

Improving the precision score of the spatial deep learning model for Scotch broom detection is crucial to enhance its effectiveness and usability. Addressing the factors that contribute to false positives, such as refining the model architecture, increasing training sample size, optimizing feature extraction, and addressing data limitations, can help improve the precision and overall performance of the model. Rigorous validation and ground-truthing efforts should also be employed to verify the accuracy of the model's predictions and ensure its reliability in practical applications.

Size of the Training Dataset:

The size of the training dataset refers to the amount of labeled data available to train the model. It plays a crucial role in determining the model's accuracy and generalization ability. Generally, a larger training dataset can provide more diverse examples for the model to learn from, potentially leading to better performance. With more data, the model can capture a broader range of patterns and make more accurate predictions. However, there may be diminishing returns as the dataset becomes excessively large, and collecting or labeling data can be time-consuming and expensive.

Assessing the impact of dataset size on model accuracy involves comparing the model's performance across different dataset sizes. This can be done by systematically increasing or decreasing the training dataset size and measuring the resulting accuracy. It helps identify the optimal dataset size that achieves the best balance between performance and resource requirements.

Choice of Hyperparameters:

Hyperparameters are parameters that are set before the learning process and determine how the model is trained. Examples of hyperparameters include the learning rate, regularization strength, network architecture, and batch size. The choice of hyperparameters can significantly impact the model's accuracy and generalization ability.

Assessing the impact of hyperparameters on model accuracy typically involves performing hyperparameter tuning. This is done by systematically exploring different combinations of hyperparameter values and evaluating the model's performance on a validation dataset. By comparing the model's accuracy across different hyperparameter settings, one can identify the optimal combination that yields the highest accuracy.

In both cases, it is essential to use appropriate evaluation metrics, such as accuracy, precision, recall, or F1 score, to quantitatively measure the model's performance. Additionally, techniques like cross-validation or hold-out validation can be employed to ensure robust and reliable assessment of the impact of these factors on model accuracy.

By systematically assessing the impact of factors like dataset size and hyperparameters, machine learning practitioners can optimize their models, improve accuracy, and make informed decisions to achieve the best possible performance.

6. Discussion

Use of sUAS Imagery for GIS Supported Deep Learning

Strengths

As is apparent throughout the bulk of this paper, sUAS imagery is incredibly high resolution and can show a level of detail that was not possible until recently. Conversely, this ability of sUAS imaging allows for better-trained deep learning models and temporal studies showing centimeters or even millimeters of land use change compared to LANDSAT imaging. sUAS-acquired imagery can provide several strengths for geospatial analysis and deep learning, including:

- High-resolution imagery: sUAS can capture high-resolution images that provide more detailed and accurate information for geospatial analysis and deep learning models. This can be particularly useful for applications that require precise object detection, segmentation, or classification, such as invasive monitoring and land use designations.
- Multi-spectral imagery: sUAS can be equipped with various sensors, including multi-spectral sensors, that capture data beyond what is visible to the human eye. This data can be used to create more detailed and accurate maps and provide valuable input for deep learning models. Therefore, this method is often preferred. However, it comes with a substantial cost compared to prosumer sUAS models, such as the Phantom 4 Pro v2.0 used in this research.
- Timeliness: sUAS can be quickly deployed to capture imagery and data, providing timely information for geospatial analysis and deep learning. This can be particularly useful for applications that require real-time or near-real-time data, such as disaster response or EBM.

- Flexibility: sUAS can be deployed to specific areas of interest, allowing for targeted data acquisition tailored to detailed geospatial analysis and deep learning applications. This flexibility allows for greater precision and efficiency in data collection.
- Safety: sUAS provides a safer alternative to piloted aircraft for capturing imagery in hazardous or hard-to-reach areas, such as steep terrain or disaster zones. This reduces risk to human pilots and provides safer and more efficient data collection.

Overall, sUAS imagery can provide valuable input for geospatial analysis and deep learning models, allowing for more accurate and detailed mapping, monitoring, and analysis of various features and phenomena.

Limitations

However, with strengths come several limitations that will impact a study or monitoring project. Unlike expensive satellite and aircraft-mounted cameras, sUAS cameras often do not have multispectral or thermal capabilities at an affordable price point. Previous research on invasives has typically relied on multispectral bands to locate specific plants at specific times of the year. Upon initial research, it would cost nearly triple for a similar platform with upgraded image-gathering capacities.

Additionally, the use of sUAS is severely limited to ideal flight conditions. Atmospheric moisture, clouds, or even strong winds are enough to ground flight operations. Given the location of this study, it was necessary to make myself available for the weather. This decision was made after 25 rescheduled missions between August and December 2022. After this point, I determined that making my schedule fluid was best. This is a limiting factor for incorporating sUAS into EBM. EBM actions generally occur during all times of the year, and being grounded removes a substantial amount of perspective and monitoring capacity. Additionally, having an FAA 107 licensed pilot on standby, will no doubt cost the organization money unless they can drop what they are doing for rapid flight missions as an extra duty. Again, this means the mission, equipment, and pilots may need to remain in a state of perpetual readiness.

Challenges

The Pacific Northwest region of the United States is known for its diverse and rugged terrain and its often-inclement weather. These conditions can present several challenges to using sUAS-acquired imagery in this region, including:

- Weather conditions: The Pacific Northwest is known for its rainy, overcast, and windy weather conditions. These conditions can limit the availability of explicit imagery and make it challenging to operate sUAS safely.
- Topography: The region's diverse topography, including mountains, forests, and coastal areas, can make it tough to use sUAS and capture high-quality imagery. Some sites may be difficult to access or require specialized equipment.
- Vegetation and tree cover: The region's dense vegetation and tree cover can obscure the ground surface and make it challenging to capture accurate imagery, particularly for object detection and segmentation applications.
- Regulatory constraints: Using sUAS for commercial purposes is subject to regulations and restrictions from the Federal Aviation Administration (FAA). These regulations may limit the altitude, location, or time of day for sUAS operations, affecting the quality and coverage of imagery.
- Data processing: The high-resolution and multi-spectral imagery captured by sUAS can result in large amounts of data that can be challenging to process and analyze. This can require specialized software and computing resources.

The challenging weather conditions, diverse topography, vegetation cover, regulatory constraints, and data processing requirements can present several challenges to using sUAS-acquired imagery in the Pacific Northwest for geospatial analysis and deep learning applications.

Comparing Monitoring Methods

All academic Scotch broom mapping studies have used manual ground truthing methods and LANDSAT imagery, including RGB and multispectral. While using sUAS is not new to environmental management, and even invasive monitoring, incorporating deep learning technology into sUAS-acquired monitoring is still in its infancy. This novel approach presents a unique opportunity when used with high-resolution sUAS-acquired imagery.

The current use of sUAS for invasive monitoring involves many of the same philosophies this research incorporates. For example, Rayonier Forestry, an international conglomerate, incorporates sUAS flights in New Zealand, the US South, and the US Pacific Northwest for forest crop monitoring. Like other agricultural and forestry businesses, Scotch broom is a common issue plaguing these full sun and disturbed sites, especially after harvest and during the first few years of full sunlight. Therefore, drone operators for Rayonier currently fly during the limited summer months while the broom is in full bloom. They then develop a rapid orthomosaic and manually prioritize the sites needing herbicide and maintenance treatments based on a manual interpretation of aerial flower density (Rayonier, 2019).

Rayonier has noted that sUAS flights have increased safety, lowered costs, and saved time in forestry by shortening the gap between harvest and planting using multispectral and RGB cameras (Rayonier, 2019). Additionally, sUAS scout ahead to determine if the terrain and roads are passable or safe for ground crews. As always, there are resolution and site size tradeoffs that should be explored for each site-specific plan.

Rayonier's research also indicates gaps to be addressed to highlight the potential of sUAS technology. Primarily among those gaps are the off-season use of drones and other imagery technique tradeoffs, such as manually searching for broom plants. LANDSAT has poor resolution among those imagery techniques compared to sUAS; however, it quickly acquires imagery for vast tracts of land at a fraction of the cost for manual or even sUAS missions (See Figure 26, below) (Skywatch, 2022). Furthermore, the cost of incorporating a piloted flight mission is exponentially greater than sUAS missions and does not support site-specific monitoring and management. Also, drone missions only occurring in the summer is another limitation because of the time between flights and Scotch broom's rapid growth potential during the Fall and Spring.

A similar study to my research was designed using image classification in Florida to track invasive cogon grass by Abd-Elrahman et al. (2021). This study used image classification rather than object detection, however, this study had powerful precision around 83%, rather than 50% using object detection. This study incorporated 2100 samples with ground truthing and a survey grade sUAS. This study showed great promise when minimizing constraints like time of year "proximity to the equator as well,, ideal image collection environments, wind, processing power, and a higher quality of the tools and other equipment used overall. Most impactfully is that this study shows that with ideal technology and sufficient processing power, this technology already provides great promise and current utility. Additionally, it supports the notion that creating a database should likely be conducted in the most ideal conditions. Those reasons are precision GPS ground control points, ground truthing, and site access will ensure precision, recall, and f1 scores that are accurate nearly 99% of the time (Abd-Elrahman et al., 2021). Supporting this further are that the sampling recommendations from ESRI are inadequate for use outside of monocrop agriculture settings.

Sampling recommendations of 600 are efficient for a proof-of-concept model, as my research shows. However, for a truly accurate model, I would argue that increasing the sampling to at least three or four times more would be more accurate and hence reliable when put into use in the field. The Abd-Elrahman et al. (2021) study used 2100 samples with ground truthing and achieved 98.5% accuracy levels on all metrics. An additional example study by Yu et al. (2019) supports increased sampling with 6000 positive images for each species trained in their model. Moreover, this study used survey grade equipment and high-power processing in the field and during processing. The processing power was employed on imagery that was captured during optimal times and lighting. It was then subsequently ground truthed for further analysis and hyperparameter optimization to achieve all metrics at 99.7% or higher. This further supports the idea that having an optimal location with site access may not be possible; however, it is clearly optimal and should be a chief priority of all site managers and mission designers. Additionally, not all study locations will require 99% accuracy, nor is 6000 ground truthed samples feasible. I believe that going from 98.5-99.7% with nearly triple the samples is not efficient for most uses except rigorous scientific experiments. An example of this might be the UAV "helicopter" on Mars, Ingenuity, where it is flying autonomously with a seven-minute delay between the planets. Less extreme but still relevant is the situation discussed regarding the Cooper Crest illegal logging. The difference of a few feet or meters could miss trees that were taken illegally and undermine the true cost of damages and restitution. However, for ecosystem management at most scales, the difference is negligible in practice.

Figure 26

Satellite vs. sUAS Imagery

Note. The left shows the most zoomed satellite imagery available on the Cooper Crest site (Maxar, July 2022). To the right is the sUAS-acquired imagery from February 2023 at approximately 245 ft above ground level (AGL). This comparison shows that the gathered resolution supports the use of sUAS for research of this nature, particularly regarding deep learning accuracy, which benefits from increased resolutions.

Comparing Traditional Invasive Monitoring

Traditional methods of monitoring invasive species involve various techniques and approaches aimed at detecting and tracking the presence and spread of invasive species. These methods often rely on manual observations, field surveys, and other forms of data collection.

Here are some commonly used traditional methods:

Field Surveys and Visual Inspections: Field surveys involve systematic observations conducted by trained personnel to identify and document invasive species. This method typically relies on visual inspections of plants, animals, or other organisms in their natural habitat. Trained observers look for specific characteristics or signs of invasive species, such as distinctive physical features, damage to vegetation, or changes in ecosystem structure. This research used a heavily modified version of visual inspections mixed with remote sensing to create and label the sampling database.

Trapping and Sampling: Trapping and sampling techniques are used to capture and collect invasive species for identification and monitoring purposes. Traps, such as sticky traps, pheromone traps, or baited traps, can attract and capture invasive species, allowing researchers to assess their presence and abundance. Sampling techniques, such as sweep netting or vegetation sampling, involve collecting samples from specific areas and examining them for invasive species.

Remote Sensing and Satellite Imagery: Remote sensing technologies, including satellite imagery and aerial photography, are used to monitor large areas and detect changes in vegetation patterns associated with invasive species. These methods can help identify areas of infestation, track the spread of invasive species, and monitor changes in vegetation over time. Satellite imagery provides broader spatial coverage, while aerial photography allows for higher-resolution images, such as sUAS acquired imagery.

Citizen Science and Volunteer Monitoring: Citizen science initiatives engage the public in reporting and monitoring invasive species. Volunteers, including community members, nature enthusiasts, or citizen scientists, contribute to data collection efforts by reporting observations of invasive species. These observations can provide valuable information on the presence, distribution, and abundance of invasive species across a wider geographic area.

Historical Records and Expert Knowledge: Historical records and expert knowledge can be valuable sources of information for tracking invasive species. Historical documents, herbarium collections, museum specimens, or scientific literature can offer insights into the historical distribution and impact of invasive species. Expert knowledge from scientists, researchers, and local stakeholders can provide additional context and guidance in identifying and monitoring invasive species.

It is important to note that traditional methods of invasive species monitoring may vary depending on the specific target species, ecosystem, and available resources. Integrating multiple methods and approaches can enhance the accuracy and effectiveness of invasive species detection and monitoring efforts. When evaluating the limitations of traditional invasive monitoring and detection methods, common issues include labor intensity, time consumption, restricted spatial or temporal resolution, observer bias, incomplete coverage and detection, resource constraints, and lack of standardization (Weidlich et al., 2020).

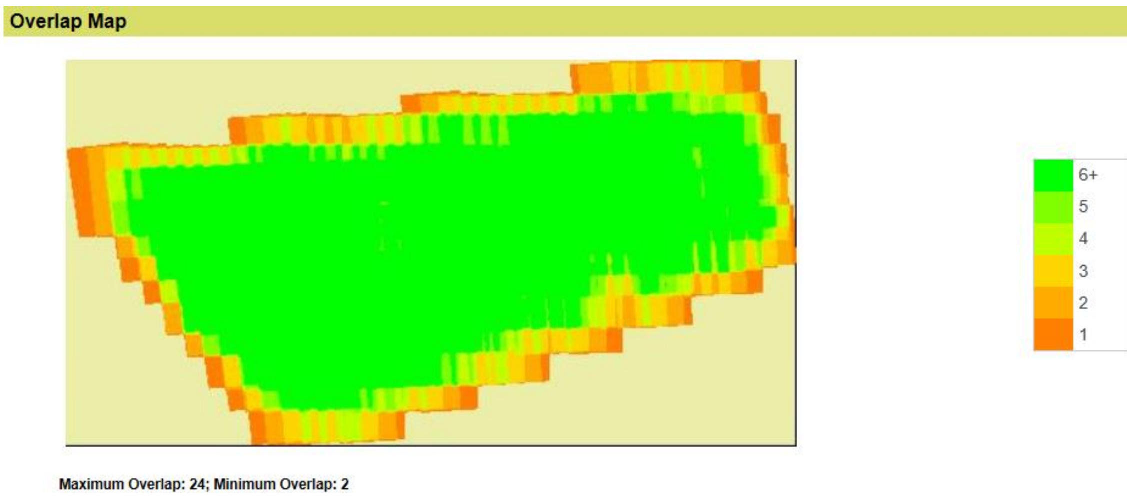
sUAS Acquired Imagery

Using sUAS-acquired imagery has many tradeoffs primarily dependent on the funding available to an individual or corporation. As is expected, a five-year-old device has limitations compared to more contemporary and better models with advanced cameras. A professional mapping drone with all the accessories may cost over $100,000. To that end, this research used these limitations as a parameter of affordability and to reduce direct operating costs.

A recommendation that may not fit all sites is a photo or image overlap. For example, the overlap map in Figure 27 below shows that the center and bulk of the site are effectively covered with an overlap density of 6+ images. This allows for generating many more tie points and a better quality orthomosaic with fewer holes, artifacts, and distortions. In addition, flying a mission pattern at least one or two flight rows wider than the site would create less edge blurring and distortions, ultimately saving time and processing by reducing the need for repeat processing.

Figure 27

Overlap Map



Note. This overlap map indicates the number of images overlapping across the invasive site. The outer edges have less overlapping and hence more issues with the orthomosaic such as artifacts, distortions, and possibly even holes in the orthomosaic. This can be remedied by flying a mission that exceeds all the site boundaries by at least one or two image captures. However, it creates a tradeoff that equates to additional energy and extended flight time requirements.

Cost

Implementing the used DJI Phantom 4 Pro V2.0 proved effective in both functionality and cost. The total price for the DJI Phantom was $1500.00 and included: a hard case, backpack, five batteries, helipad, remote control, iPad attachment, spare propellers, and the required cords. In addition, the Phantom 4 flight software from ESRI and DJI are all free for personal use as of this writing. However, with incremental iPad and iPhone iOS updates, I have noticed that the program is becoming more unstable, which is common in situations with legacy software or hardware (McCarty, 2019). Therefore, I recommend using a company-supported flight application, as DJI GS Pro is now in legacy status and no longer receives updates.

The most recent update to iOS in January- February 2023 has caused many severe issues between the software and the sUAS. During flight operations using GS Pro, and somewhere around the 50-60 image collection mark, the program force closes, and sUAS control is subsequently lost. A quick workaround is immediately opening the program and putting the sUAS in sport mode. Unfortunately, the flight planning software does not require a full mission upload from the remote control, which means the mission still runs while the remote control has lost contact with the sUAS. This was observed as the sUAS continued to move, stop, shoot, move, etc. Because of this, the operator must manually move the sUAS at least one meter from its last known position and restart the mission. Thankfully there are other free alternatives, such as ESRI SiteScan LE or PIX4Dcapture, among many other competitors. All of which can perform the same functions, except stopping to acquire imagery, which is still a DJI trade secret of this writing.

Implementing the Geode into this research came with a total price of approximately $3000. While the price may seem high, the cost of popular competing brands ranges from $5000 to $20,000 for slightly better functionality. Some alternative options may have been better suited if centimeter-level accuracy were needed. However, implementing high-resolution sUAS imagery combined with this GPS product created sufficient precision for this research at a fraction of the potential cost where it was incorporated. I will state that not incorporating a GPS device severely constrained this research. However, that was the intent. In addition to GPS devices, designing and testing surveys for ground truthing are necessary to mitigate issues during enumeration.

Quality survey design is essential; balancing the trade-offs between function and ease of use associated with survey enumeration was a challenge in this regard. Preliminary research for this project at the Cooper Crest site found that precision GPS positively affected not only the survey's authority, but the elevation models and orthomosaics during the summer and early fall months substantially, but less so during the winter and spring. Additionally, enumerating the surveys took approximately 10-15 seconds per encounter in the rain and around five seconds in dry weather. The initial survey designs with mandatory photo captures took an average of 30-45 seconds. At first, this seemed negligible; however, for every group of one thousand surveyed items, an average increase of 15 seconds per stop adds 15,000 seconds of surveying time or 250 hours. This did not consider distances between plants, terrain features, or weather. Ultimately, a survey is site dependent, and this research found that spending a small amount of time on survey design saved countless hours on the back end. Furthermore, incorporating the Geode level of accuracy allowed for troubleshooting on-the-fly and self-correction for on-ground enumerators when applicable at the Cooper Crest site.

Survey design is also crucial for costs, as adding 250 more hours will have a price associated with it. Some of these basic costs include the time to design the survey. For example, the invasive tracker survey I created took around two hours to develop and troubleshoot and was relatively simple by design. Additionally, enumerating 250 additional hours requires volunteers or paid employees. I would argue that the use of volunteers would be effective. However, training and discrepancies from the extended amounts of enumeration time may be costly, with insufficient data or duplicates costing additional processing times and increased costs. Then there are the costs associated with training which depend on various metrics outside the scope of this research. Even enumerating a single survey once per month with 250 additional hours equates to 3000 hours annually. The cost becomes impactful when adding payroll information at, say, $20.00 hourly wages, which equates to $60,000 in unnecessary costs annually from the survey alone. Multiply this over the lengthy timelines of a restoration project, and the additional costs could be in the millions.

There are also rental options for those unable to purchase a Geode unit. Given that it is possible to use the same GCP repeatedly, acquiring permanent GCP locations using a rental unit can provide submeter GPS services as long as the GCPs are visible on future flights. Drone2map has a specific workflow for coregistration, which georeferences one project off another with relatively high precision, limited only to the accuracy of the original orthomosaic. Additionally, ArcGIS Pro can accept .csv or .txt files, among several other GCP inputs. A recommendation for this workflow would be creating permanent GCPs and using Survey123 to acquire those locations with either a rental or owned GPS unit (See Figure X below). Adding these points with Survey 123 into the ArcGIS Pro workflow will save significant time and money in preparing and processing as they are all part of the ESRI suite and seamlessly integrate. Fondriest Environmental Inc. has the most competitive rates, from $64.00 per day to $386.00 per month (Fondriest Environmental Inc., 2023). Competitors range from $115-250 per day to $325-500 monthly.

Figure 28

Permanent Ground Control Point

Note. Here is an excellent example of a ground control point (DJI Enterprise, 2022). Creating permanent structures such as these on a site is recommended to minimize costs. This would be even more beneficial if renting a GPS unit because one could easily collect all the GCPs for all future flights at a site if the GCPs are sited and constructed effectively. This could save a factor of ten if using a Geode rental, possibly even more if using a Trimble or other survey-grade unit.

Additionally, ESRI offers free or reduced cost geospatial software for qualifying nonprofit organizations in the USA. For non-qualifying organizations, the GIS Professional Advanced license cost is currently $4150 per year unless it is part of an educational institute. Additionally, the ArcGIS Pro all extensions bundle is $1950 per year; this enables all the extension tools within the desktop application for users with cheaper subscriptions or free accounts. These tools are required to classify, train, and deploy the model and its geoprocessing functions. Another useful ESRI tool is drone2map. However, drone2map is an additional $1750 per year on top of the other costs required to run and use the deep learning packages. While these products are not cheap, they can conduct spatial analysis and other geographically oriented problems.

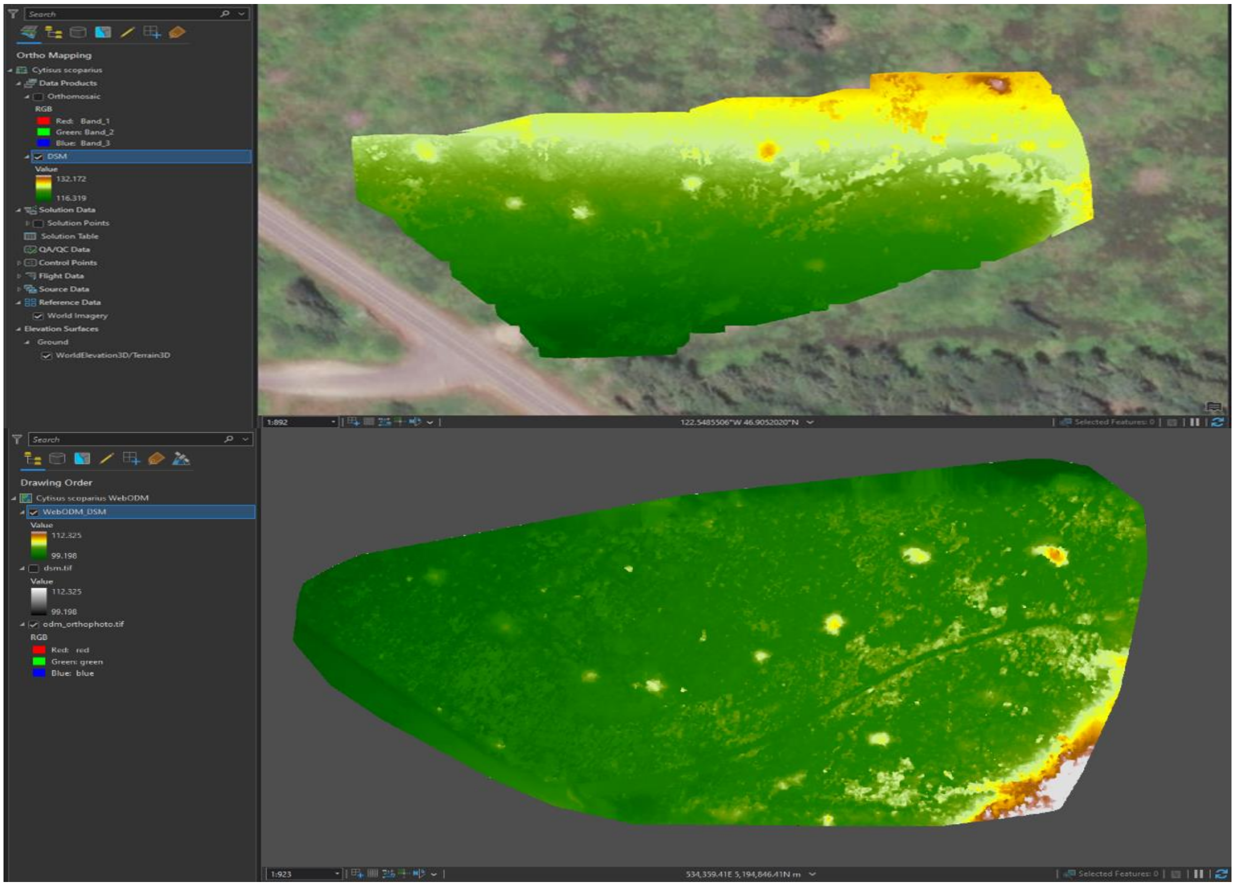
DSM

When comparing DSMs derived from ArcGIS Pro and WebODM, there were discrepancies in the mean Z or elevation variable. Figure X below shows the differences in elevation using the same color scheme. The lowest elevation in the ArcGIS version was 116.319 meters above sea level, compared to 99.2 meters for the WebODM-derived product. For example, a control at the site had an approximate elevation value of 423 ft using Google Earth Pro and the USGS Topographical map elevations. The exact location was approximately 409.37 ft on ArcGIS Pro and 340.65 ft using WebODM.

What was determined is that WebODM inherently captures the features, including terrain, slope, and elevation variation, better than ArcGIS Pro in every tested location. However, ArcGIS Pro better incorporates the site's mean sUAS elevation data into the geoprocessing. While neither is perfect at capturing the elevation given the parameters and settings I incorporated, both do a respectable job without using precision GPS units, such as the Geode. The Geode single-band receiver has around six feet of vertical error, about double its horizontal error (Juniper Systems, 2021). Using the Geode with several GCPs visible in the aerial imagery would also make processing more effective by including the tie points from the GCPs for both ArcGIS Pro and WebODM. This would help capture the elevation more and possibly make the resulting orthomosaic higher quality.

Figure 29

DSM Comparison



Note. These juxtaposed images show the elevation banding in ArcGIS Pro (topmost) compared to the WebODM-derived DSM (bottom). These images also show the additional detail WebODM picked up with the RGB sensors compared to ArcGIS Pro. However, ArcGIS Pro captures the mean site elevation better, even with some discrepancies.

Implications and Applications

When using a constrained deep learning model with only precision available as the evaluation metric, there are several limitations and considerations to keep in mind:

Trade-off with Recall: Precision measures the proportion of correctly predicted positive instances among all instances predicted as positive. However, it does not consider false negatives (incorrectly predicted negatives). In some cases, a model with high precision may have a low recall (proportion of true positives predicted correctly), indicating that it misses a significant number of positive instances. It is crucial to strike a balance between precision and recall based on the specific requirements of the application.

Imbalanced Data: Precision alone may not adequately capture the model's performance when dealing with imbalanced datasets. Imbalanced datasets occur when the number of instances in different classes is significantly skewed. A high precision score can still be achieved by correctly predicting the majority class while neglecting the minority class. In such cases, additional evaluation metrics like recall, F1 score, or area under the precision-recall curve should be considered to gain a comprehensive understanding of the model's performance.

Limited Insight into False Negatives: Precision does not provide direct information about false negatives, which are instances that are incorrectly predicted as negatives. False negatives may represent critical instances that the model fails to identify. Without considering false negatives, it is challenging to assess the model's capability to detect all positive instances accurately.

Application Context: The choice of evaluation metric should align with the specific requirements and goals of the application. Precision might be suitable in scenarios where minimizing false positives is crucial, such as spam email detection. However, in other applications where missing positive instances is a significant concern (e.g., medical diagnosis), precision alone may not provide sufficient insight.

Model Optimization Bias: Relying solely on precision during model development and optimization may lead to a bias towards optimizing for high precision at the expense of other performance measures. It is important to consider a broader set of evaluation metrics to ensure a well-rounded assessment of the model's performance.

To overcome these limitations, it is recommended to consider a comprehensive evaluation approach that incorporates multiple evaluation metrics, including recall, F1 score, accuracy, and area under the receiver operating characteristic curve (AUROC) or (ROC) analysis. This allows for a more thorough assessment of the model's performance, particularly in constrained deep learning scenarios such as this research.

Future Directions

The future of spatial deep learning in ecosystem management holds great promise for advancing our understanding and conservation of natural environments. One prominent direction is the application of spatial deep learning in mapping and monitoring biodiversity. By analyzing high-resolution satellite imagery and drone-acquired data, deep learning models can assist in identifying and classifying species, mapping habitats, and monitoring changes in biodiversity over time. This can provide valuable insights for conservation planning and the assessment of ecosystem health.

Another area of growth lies in the integration of spatial deep learning with environmental sensing networks. By combining deep learning algorithms with data from sensors deployed in ecosystems, it becomes possible to detect and predict environmental changes and their impact on ecosystems. This can aid in early warning systems for environmental disturbances, such as invasive species outbreaks or habitat degradation, enabling proactive management strategies.

Spatial deep learning also has the potential to enhance the precision and efficiency of ecosystem monitoring. By automatically analyzing vast amounts of spatial data, including satellite imagery, sensor readings, and geospatial databases, deep learning models can extract meaningful patterns and trends. This can help identify critical areas for conservation interventions, optimize resource allocation, and support adaptive management approaches.

Furthermore, the integration of spatial deep learning with citizen science initiatives has the potential to amplify the capacity for ecosystem monitoring. Citizen scientists can contribute observations and data, which can be processed using deep learning algorithms to scale up monitoring efforts. This collective approach can enhance spatial coverage, improve species identification accuracy, and foster public engagement in ecosystem management.

The future of spatial deep learning for ecosystem management also lies in the development of decision support systems. Deep learning models can aid in analyzing complex ecological data, simulating scenarios, and predicting ecosystem responses to different management actions. This can support evidence-based decision-making, enabling more effective and sustainable management strategies.

In summary, the future of spatial deep learning for ecosystem management holds immense potential. Through its application in biodiversity mapping, integration with environmental sensing networks, precision monitoring, citizen science, and decision support systems, spatial deep learning will likely contribute to our understanding, conservation, and sustainable management of ecosystems. It will facilitate more accurate assessments of ecosystem health, inform conservation actions, and assist in mitigating the impacts of environmental change on our natural world.

Improving Accuracy and Efficiency in the Future

Future research testing the integration of sUAS, and deep learning techniques holds significant potential to benefit EBM. sUAS provides a valuable platform for collecting high-resolution spatial data, such as aerial imagery and remote sensing data, which can contribute to more accurate and detailed ecosystem assessments. Deep learning, a subset of artificial intelligence, offers advanced capabilities for analyzing and extracting meaningful information from large and complex datasets. By combining sUAS imagery with deep learning algorithms, researchers can enhance the speed and accuracy of data processing, allowing for efficient identification and classification of key ecosystem components, such as habitat types, species distributions, and invasive species. This integration has the potential to improve the precision and efficiency of monitoring efforts, aid in decision-making processes, and support adaptive management strategies in EBM. Additionally, as technology and methods evolve, continued research in this field can lead to the development of innovative tools and approaches that further enhance our understanding and management of ecosystems.

For policymakers and practitioners interested in implementing sUAS and deep learning into EBM, several recommendations can guide their efforts. Firstly, fostering interdisciplinary collaborations between ecologists, remote sensing experts, and data scientists seems essential. This collaboration will help ensure the integration of ecological knowledge, technological expertise, and data analysis capabilities. Secondly, investing in training programs and capacity-building initiatives for sUAS operation, data collection, and deep learning analysis is crucial to ensure proficiency and maximize the benefits of these technologies. Thirdly, establishing standardized protocols and guidelines for sUAS deployment, data collection, and deep learning analysis will enhance consistency, comparability, and data quality across different EBM projects.

Additionally, policymakers should support research and development efforts to advance sUAS capabilities, image processing algorithms, and deep learning techniques specific to EBM needs. Lastly, considering ethical and privacy considerations surrounding data collection and sharing is vital. Policymakers should develop frameworks to ensure the responsible and transparent use of sUAS and deep learning technologies. By following these recommendations, policymakers and practitioners can harness the full potential of sUAS and deep learning in EBM, facilitating more efficient and effective ecosystem management strategies.

7. Conclusion

Incorporating sUAS-acquired imagery, workflows, and methodology-supported profound learning show promise for integration into ecosystem-based management (EBM) phase IV and locating invasive plant species. The results of this research did show the limitations of constraints such as: low solar zenith angle, RGB imagery only, poor weather conditions, site accessibility, low processing power, and minimal invested costs. However, despite those constraints, the supporting products required to classify and train a visual model showed substantial promise and effectiveness toward automated invasive detection. Based on this perspective, sUAS shows promise for every phase of EBM. The value will depend on the availability of finances, trained personnel, and real-world limitations such as weather, site availability, and technology access. Historically, access to technology and adequately trained personnel have been a crux for EBM and related disciplines, which greatly inspired my research into accessibility (Carabassa et al., 2021). This partly inspired this research as the physical equipment is publicly available, and ESRI and the WebODM geographical information systems (GIS) community fully support the resources and workflows used within. EBM is community-focused, and keeping these technical products effectively fills this niche.

The average ground sample distance (GSD) was approximately 5cm for the elevation models and orthomosaics. A 5cm GSD is around three times greater when compared to the most cutting-edge satellite and piloted aircraft surveys. Based on real-world experience, summer flight operations will produce substantially better orthomosaics with fewer artifacts and 1-2cm GSDs, further outperforming these fall-spring flights and the alternative remote sensing methods often used. This may also benefit invasive identification by locating younger plants before they can reproduce.

The resulting deep learning object detection model also showed promise with a 49% precision score for object detection. Remember, precision aims to determine the accuracy of identification by assessing the true proportion of Scotch broom labeling. It effectively investigates whether the Scotch broom is correctly labeled or mislabeled. It is important to note that 49% is considered very low and unusable in many situations, with 50% often being a lower limit (Google Developers, n.d.). However, these research constraints indicate that a site manager may sufficiently map an area in real-world applications with real-world limitations. Additionally, this is possible without ever stepping on site while effectively processing the imagery, supporting products, and deep learning model in one to two days. This might be considered hasty; however, the ability to rapidly incorporate a nadir perspective with basic geography and invasive identification benefits all the phases of EBM.

These benefits may include visual models and products to support the community goals of a project or better inform environmental policy and management more efficiently. Also, having these products benefits risk assessments and increases knowledge bases by showing the general geography, slopes, grades, locations of water, and other notable features, including the prevalence of invasives that are often easy to spot. Increasing the efficiency of applied EBM will simultaneously reduce costs while supporting phases III and IV about the EBM plan and its long-term application. Similarly seen in systems thinking design, a more effective model will ideally create a positive feedback loop that benefits management over time, even in the off-season.

While this off-season method is insufficient for survey work, EBM often prioritizes safety, personnel availability, and costs with little need for centimeter accuracy requirements. Typically, when those situations arise, such as the litigation sought by Olympia for the illegal logging at the Cooper Crest site, a surveyor would evaluate the property boundaries and establish legal standing or ownership within applicable laws and regulations. However, this skillset and title requires nearly six years to a decade of school and internships. Therefore, it is outside the scope of this research to discuss beyond mention (Board of Registration for Professional Engineers and Land Surveyors, 2021).

I argue that a professional surveyor with better equipment could incorporate real-time or post-processing kinematics alongside these methods to generate a model with exponentially greater potential. This would, in turn, accelerate the benefits to EBM. However, the costs associated with survey-level mapping are exponentially more expensive. This model helps fill that gap by annotating stands of Scotch broom that are then easily grouped using a geoprocessing buffer tool. This tool could then be used to prioritize crews and management for all phases of EBM meaningfully. Again, this is especially true for phase IV. However, it could be applied to additional invasive and endemic species to delineate their differences and establish priorities, increasing the costs and time associated. This is important in the Pacific Northwest and many other locations, as site safety and other hazards often prevent effective EBM from occurring even though it is warranted. Being able to use a combination of geospatial tools and object detection models has the potential to minimize accidents and simultaneously cut costs for management teams on the ground.

I also argue that training an extensive database from many regions with multiple species and classifications would support statewide EBM. A publicly available download with endemic and invasive species has the potential to save millions of dollars statewide for any entity with a need for geospatial analysis, such as the DNR, NOAA coastal monitoring, or other public, private or government agencies.

Additionally, the costs associated with sUAS vary depending on the needs of a site or industry. This research indicates that a low-cost and used sUAS can perform sufficiently enough to create usable elevation models and orthomosaics. Although, it is essential to note that these products are not survey-grade because of the lack of centimeter-level precision GPS. This research may be conducted with an upfront cost of less than $2000 for the sUAS. Additionally, it would cost approximately $3000 to incorporate the applicable programs for deep learning. For precision GPS-required sites, those costs vary as well. However, this research found that a $3000 Juniper Geode performed admirably with submeter precision. Furthermore, there are cost-reduction opportunities for needed equipment. For example, an environmental manager could incorporate permanent ground control points and use rental equipment, sUAS, GPS, etc., to establish a site baseline for substantially less money and at intervals that suit their community and site-specific goals.

The supporting products and workflows strengthened model construction using the recommended 600 samples. The streamlined process takes approximately 1-2 days to complete, including preflight safety checks, mission planning flight times, and processing. Classifying, labeling, and training the model with 600 samples and manual verification took approximately three, two, and five hours in the same order. Again, this model was about 50% effective at identification. However, I argue that the suggested sampling size based on the degrees of freedom is not practical for object detection within EBM, at least within the constraints of this research. From 60 to 600 samples, the recall increased from 31 to 49%, a substantial gain. However, I hypothesize it will perform better with increased sampling at even greater resolutions as supported in additional studies (Abd-Elrahman et al., 2021; Yu et al., 2019). This is especially true if a manager can mitigate known constraints. Examples include flying overhead at noon during the summer months with homogeneous cloud cover to limit shadows and shading effects from the movement of the sun and flight times. Additionally, using precision GPS and having either the team or time to conduct thousands of survey enumerations will benefit the model. Furthermore, each site is different regarding geography, community goals, and the laws and regulations of the region.

In the future, I propose that creating a highly effective model will likely require around 4000 samples following a similar sampling protocol to those seen in another study using deep learning image classification (Abd-Elrahman et al., 2021). In addition, these and a separate training site should then be manually ground-truthed for further validation using ArcGIS Pro. This means a safe and accessible location with a sufficient nadir view will make the best database sampling site and sufficient time or personnel with training and equipment. In addition, having substantial ground-truthed points would allow for further analysis and highly accurate precision, F1, and recall values seen in highly modified environments, such as palm oil plantations or urban environments.

In conclusion, while this model was not the 99% effective I dreamed about, it is halfway there. I fully understood the immense challenge of planning sUAS flights during the rainy fall-spring in Washington. However, creating a visual, step-by-step model will guide further research into invasive management and EBM. I am fully committed to expanding this research with volunteer opportunities over the next few years and establishing a packaged model that can be easily deployed within a nonprofit or state GIS program. My vision is to allocate tax money better and prioritize sites for remediation or protection, such as our beautiful mountain valleys and coastal regions under various stressors, before they pass a tipping point. Monitoring and effectively mitigating invasive species before they take hold will benefit the local ecosystems and likely the economy with minimal inputs compared to taking a reactive approach and focusing on remediation. As a trained environmental manager, I will end with my favorite quote pertaining to invasive mitigation and remediation and wish anyone reading this the best of luck in their future endeavors:

"*An ounce of prevention is worth a pound of cure.*"

(Benjamin Franklin, 1736)

Figure 30

Cytisus scoparius on Bald Hill Road

Note. Cytisus scoparius on Bald Hill Road near my home in Yelm, WA with Mount Rainier in the background.

8. References

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