Using drones and image classification tools to map complex coastal habitats along the upland-subtidal gradient in Massachusetts embayments

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Abstract

Natural resource managers conduct various habitat mapping activities to inventory, monitor and manage natural resources and habitats. Habitat mapping efforts are typically done with a combination of remotely-sensed imagery (e.g. collected via satellite or aerial fly overs) and on-the-ground surveys. In the past decade, unmanned aerial vehicles, or drones, have become more readily available and easier to deploy. Their use in agriculture and forestry management has become commonplace, but application in coastal and marine environments is still in development. This study tests the efficacy of using an off-the-shelf consumer drone as a meso-scale habitat mapping tool for the purpose of quantifying and visualizing habitats within the gradient from upland beach to marine subtidal areas at three sites in northeastern Massachusetts. Each study site consists of subtidal eelgrass and at least five other habitat types to achieve the desired habitat complexity, including coastal beach, rocky intertidal, submerged algae, submerged rock, submerged sand, salt marsh, dunes and wrack. Sites were flown during the summer growing season (2020) and winter dormancy (2021) to assess the ability to detect temporal variations in habitat extent.

Supervised object-based image analysis (OBIA) was performed to classify the various habitat types based on spectral and spatial properties. The Support Vector Machine classifier performed best in accuracy assessments, and was trained using groundtruthing data and existing state-produced habitat maps. Very high resolution (~2.5 cm/px) drone-derived imagery was found to produce exceptionally detailed habitat maps through image classification, and all studied habitat types were able to be detected by the classifier. The acreage, extent and intra-habitat spatial distribution were able to be tracked over time. Some habitat types had consistently high classification accuracies, such as eelgrass and rocky intertidal (85.3% and 81.0% mean accuracy, respectively) and others had consistently lower accuracies such as submerged algae (20.0%) and salt marsh (30.3%). Low accuracies may have been caused by small sample size, image quality issues, and errors in reference and/or groundtruthing data; with these pitfalls addressed, better classification performance would likely be achieved. Finally, the same drone imagery was manually interpreted for eelgrass and salt marsh using a Heads-Up approach to assess the use of integrating this data source into ongoing aerial survey that are used to track these habitats on a state-wide scale. The Heads-Up approach was far more rapidly executed, and provided similar habitat extent information to that of the machine classifier, at the cost of losing more accurate acreage data and intra-habitat distribution information (e.g. vegetation patchiness).

An imagery workflow and recommendations are shared regarding methods and applications of drone technology that coastal resource managers can use when designing habitat mapping programs.

Chapter 1. Introduction

Coastal habitats are areas that provide marine, estuarine and near-shore plants and animals with their requirements, including food, shelter and suitable environmental conditions for maintaining life. With 78 coastal communities along 1,500 miles of shoreline, Massachusetts has a robust “Blue Economy” that relies on coastal areas to support fisheries, recreation, tourism, transportation and marine commerce.[1] With so many uses overlapping with and relying upon coastal habitats, it is paramount that such habitats are adequately catalogued and managed to ensure the persistence and growth of a sustainable Blue Economy.

Resource managers in the coastal zone have the challenge of working in a highly dynamic environment that is ever-changing due to natural and anthropogenic processes. At the boundary where land meets sea, the hydrography, exposure, geology and anthropogenic characteristics define what habitats can prevail and how they change over time. Further complicating resource management is the interconnected nature of coastal habitats, in the sense that water, nutrients, sediment, biota and even pollution often transfer from one habitat to another.[2] This interconnectivity makes an ecosystem management approach much more effective than single-species or single-habitat management.[3] With climate change expected to deliver larger storm surges, more coastal infrastructure damage, and greater impacts to fisheries and tourism in Massachusetts[4], the need to track changes to coastal habitats in an ecosystem context has never been greater.

Many states inventory coastal habitats using a variety of *in situ* and remote data collection methods. For example, beach and dune habitats can be monitored to assess erosion, accretion, and coastal storm damages to evaluate climate change impacts. The extent and condition of vegetated habitats like salt marshes and eelgrass can be tracked as sentinels for water quality, hydrology and environmental health. Coastal habitat mapping can also provide baseline data prior to a proposed impact, such as the installation of stormwater outfalls, utility pipelines, seawalls, piers, or other structures, and provides a means of assessing impacts post-construction. For all mapping efforts the appropriate method, scale and data resolution are dictated by the intended use of the data.

As such, coastal habitat mapping strategies can be thought of as interactive and supplemental steps within a hierarchy. In this hierarchy, small-scale (e.g. less detail over larger area) habitat mapping often relies on imagery collected by satellite or manned aerial flights. Meso-scale mapping offers more detail and uses higher resolution aerial imagery, and can involve other remote sensing techniques such as side scan sonar in subtidal areas or lidar in uplands and shallow subtidal areas. Large-scale (i.e. greater detail over a smaller area) mapping typically involves *in situ* measurements, with scientists performing habitat delineations and collecting plant-level morphological and/or sediment characteristic data. Each step in the hierarchy has its share of benefits and shortfalls. Small-scale imagery can be expensive to procure, tied to fixed schedules, overly coarse in resolution, or made unsuitable due to weather or tide conditions during collection. Due to these limitations, mapping frequency may be low, but the payoff is data coverage over a large survey area. On the other hand, large-scale mapping can be cost prohibitive and hazardous, especially when working in subtidal environments where divers are required or where there are access or safety concerns. Data from this scale provide a high level of detail that might only be relevant to a particular stretch of shoreline, and thus not transferrable to other areas of interest. Meso-scale mapping methods fall in between, offering a moderate survey area size and moderate level of detail. Drones offer a lower-cost, higher resolution (< 5cm), and more rapidly-deployed means of acquiring imagery compared to manned flights and satellites. While collecting plant or soil metrics may not be practical with a drone, in terms of habitat extent mapping, a drone survey can cover a far greater area in less time compared to *in situ* habitat delineation. For these reasons, drones may be a highly useful meso-scale supplement that help fill temporal and spatial data gap in small- and large-scale mapping efforts.

Many coastal habitat mapping programs use manual interpretation techniques to draw boundaries around distinct habitat areas visible in imagery. Manual techniques can be time consuming, require specialized training, and can be subject to human error where habitats are spectrally difficult to differentiate. Machine image classification techniques can standardize and streamline the image processing workflow, while potentially increasing spectral and spatial acuity in habitat delineations. Use of machine classifiers on drone imagery are tested here to assess their ability to differentiate and quantify habitats along the upland-to-subtidal coastal gradient.

The goal of this study is to examine the utility of using drone-derived imagery and machine classification techniques to inventory, visualize and track changes among coastal habitats. The following chapters include a literature review of coastal habitats, mapping strategies, and a review of drone technology within the habitat mapping context; followed by a detailed review of project methods, results, and a discussion focused on the strengths and pitfalls of using drones and machine classifications to map coastal habitats.

Chapter 2. Literature Review

2.1 Coastal habitats at the land-sea interface

While many distinct habitat types exist along the coast, this study specifically investigates coastal beach, submerged sand, salt marsh, rocky intertidal, submerged rocks, eelgrass, wrack, algae and dunes (Fig 1). The following subsections describe the characteristics of each habitat.

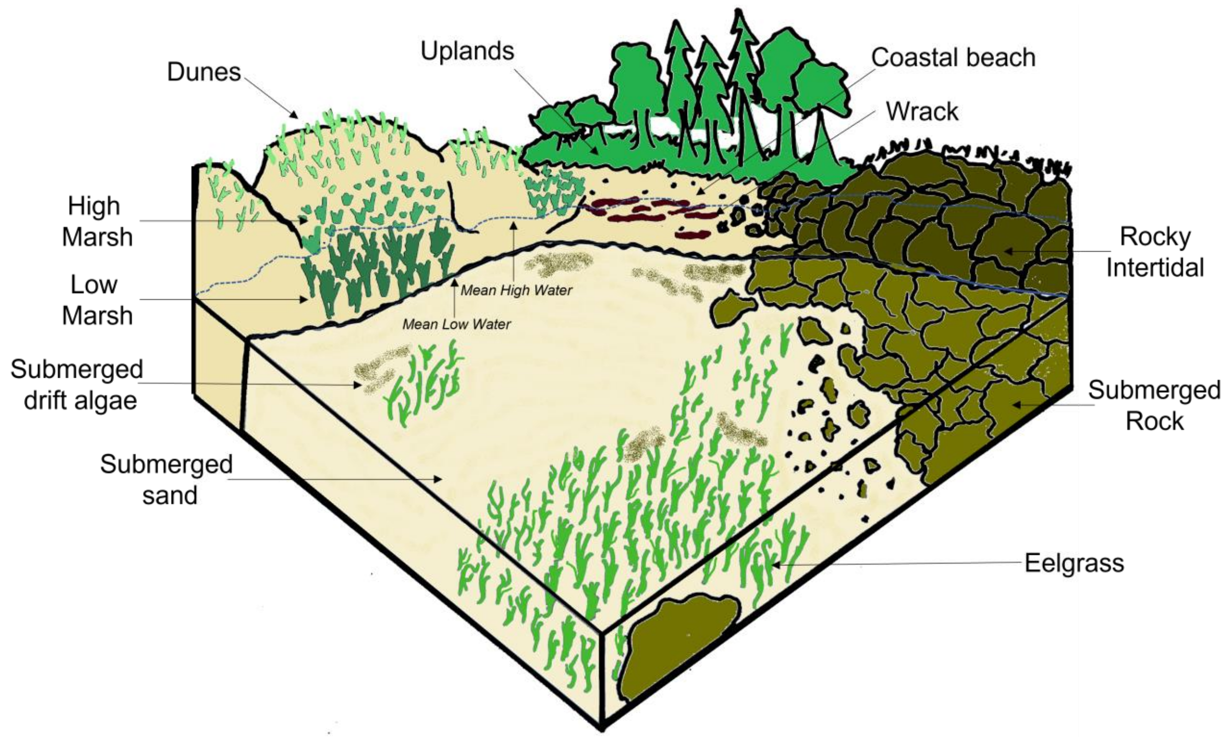

Figure 1. Diagram of coastal habitats from the upland to subtidal gradient.

2.1.1 Coastal beach

The coastal beach is an area of unconsolidated sediment that is subject to wave, tidal, and storm action, which shape the beach into a sloping profile between the ocean and uplands. Coastal beaches are most prevalent where glacial materials provide a supply of sand, gravel and cobble; though some are nourished by the delivery of inland erosional material delivered to the coast via rivers[3]. By definition, coastal beaches extend from the mean low water line to the nearest coastal bank, dune line or existing man-made structures[5]. An important area of sediment supply and exchange between nearshore subtidal areas and upland dunes, the coastal beach often is comprised of fine-to-coarse sand but can also contain gravel and cobble[2]. The granular sediment, permeability and often gentle slope of beaches can dissipate storm and wave energy and protect upland habitats from damages and flooding. Thus, the extent and condition of the coastal beach can indicate effects of climate change, sea level rise and coastal storm impacts such as erosion.

The ecological importance of coastal beaches includes supporting bird nesting, seal haul outs, shellfish habitat, and habitat for a myriad of invertebrates lower on the food chain[5]. Some coastal beaches include tidal flats, which are areas with nearly level topography, usually extending from the mean low water line to a more steeply sloped beach. Tidal flats can contain significant marine fisheries resources including shellfish, and can be vital feeding and nursery grounds for other important fish and wildlife species[5].

Where the sands of the coastal beach continue seaward below the reach of the tide, subtidal sand habitat is also important forage grounds for shorebirds, fish and crustaceans. Submerged sandy areas support countless bivalve, worm, snail, sand dollar, shrimp and lance species that are prey to commercially important species higher on the food chain[2].

2.1.2 Salt marsh

Salt marshes are coastal wetlands that contain salt-tolerant plants that are inundated regularly by the tide[6]. They provide significant wildlife and fisheries habitat, such as waterfowl nesting and grazing, finfish nursery grounds, and habitat for a variety of shellfish and invertebrate species. Common inhabitants include mummichogs, striped bass, winter flounder, menhaden, quahogs, mussels and oysters[2], in addition to countless species supported seaward of marshes where their productivity is transferred as food[3].

Salt marshes buffer the coast from storm and wave energy, remove pollutants and store carbon as water filters through the vegetation and underlying substrate - often a thick layer of peat[3]. Heavy metals, hydrocarbons, nitrogen and phosphorous can all be captured in this filtration process[5]. Peat also serves as a barrier between the subterranean water table and the ocean, providing protection and buffering to fresh water supply for human use[5].

The landward extent of a salt marsh is typically located along the highest high tide line (e.g. submerged only during the highest tide of the year) and can extend seaward to the mean low water line. The marsh is often divided into high marsh and low marsh vegetation communities (Fig 1), where the low marsh sits at a lower elevation and is inundated more frequently[3]. In Massachusetts, the low marsh is often dominated by smooth cordgrass (*Spartina alterniflora*) in its tall form. The high marsh, reached by salt spray and very high tides, is flooded less frequently and is often dominated by smooth cordgrass (*S. alterniflora*) in its short form along with saltmeadow cordgrass (*S. patens*), spikegrass (*Distichlis spicata*) and blackgrass (*Juncus gerardii*)[2]. Pollution runoff, sea level rise, hydrologic alterations and coastal construction are the primary stressors to salt marsh habitat[2], and have led to global declines[7].

2.1.3 Rocky intertidal

Much of Massachusetts' North Shore is characterized by rocky coastlines, where glaciers retreated and scoured away soft sediments after the last ice age and high wave action prevents modern sediments from settling[2]. Rocky intertidal habitat is comprised primarily of bedrock and boulder areas that are situated between the mean high and mean low water lines (e.g. the intertidal zone)[6]. In some cases, rocky intertidal habitat is man-made, such as with rock jetties, groins and rip-rap shorelines[3]. Often, these rocky areas are both emergent and submergent beyond the intertidal zone, extending into the uplands as well as underwater.

These areas provide significant storm and flood protection by reflecting wave energy, and provide abundant floral and faunal habitat in the interstitial spaces between and irregular surfaces of rock formations. Various invertebrate species thrive here, such as snails, mussels, barnacles, and snails, attracting and feeding larger fish and crustacean species as well as shorebirds and seals. Macroalgae, or seaweeds, play a dominant role in the productivity of this habitat, and include rockweed, knotted wrack and Irish moss that are able to attach themselves directly to the rocks[3]. Rocky intertidal areas also provide the unique habitat known as rocky tidepools, which are small pools of seawater left along the rocky shore when the tide recedes, supporting various invertebrates, crustaceans and small fish until the pools are inundated again[3].

Where rock extends below the tide, subtidal rocks provide prime forage and shelter habitat for lobsters, crabs, urchins and a variety of finfishes like cod[2]. In addition, an assortment of attached species of kelp, tunicates and anemones can be found here, many of which rely specifically on submerged rock habitat and cannot survive elsewhere[2,5].

For the purposes of this mapping project, algae anchored to intertidal or subtidal rocks is included in those habitats, rather than classified separately.

2.1.4 Eelgrass

Eelgrass (*Zostera marina)* is a meadow-forming flowering marine plant (i.e. a seagrass) that grows in relatively sheltered embayments, and expands via subterranean rhizomes as well as by seed dispersion. Meadow density and extent can expand and contract seasonally, with a near-dormant period in the winter, and accelerated expansion and growth in the spring and summer[3]. Throughout and especially after peak growth, older leaves and plants break off from the meadow and settle as detritus in nearby areas or are washed up on shore[3].

Eelgrass is broadly distributed in the Northern Hemisphere, but meadow location and extent are strongly constrained by light penetration (and thus depth), energy dynamics, sediment type and water quality conditions[2]. Eelgrass meadows provide multiple ecosystem benefits in estuarine systems: they support biodiversity, attenuate wave energy, stabilize and oxygenate sediments, sequester carbon and nutrients, and filter the water column[8]. Meadows and patches create important habitat, providing shelter and forage for many commercially important marine fish and shellfish species such as bay scallops, lobsters, winter flounder, tomcod hake and cod[2,9,10]. While only making up 0.2% of the area of the oceans, seagrass meadows (including eelgrass) bury 10% of the annual total estimated organic carbon sequestered in the oceans[11], providing a valuable climate change service. Because of its acute sensitivity to anthropogenic and environmental stressors, eelgrass extent is sometimes used as an aquatic health indicator in waterbody assessments[12].

Declines in seagrasses are occurring globally[7], and rates of decline have accelerated over recent decades[13]. In Massachusetts, even though eelgrass is afforded some protections by state and federal regulation, a study by Costello and Kenworthy[14] found a decline in eelgrass in 30 out of 33 embayments over a period of 12 years. Losses are often attributed to anthropogenic stressors that reduce available light needed for plant photosynthesis, such as nutrient runoff and sedimentation from coastal development[9]. Other causes can include physical displacement related to marine dredging, dumping, boat anchoring, and weather-related impacts[2].

2.1.5 Wrack

Marine wrack is a complex mix of live and dead flora and fauna that is deposited on shore as the tide recedes. Often in long bands between high and low tides, the “wrack line” can include live and dead algae, salt marsh vegetation and eelgrass that has been uprooted or detached as a normal part of its lifecycle. Wrack also includes seeds from coastal and marine plants, offering a means of seed dispersal and habitat expansion[15]. Within the wrack, an assortment of small crustaceans, bivalves, snails and other organisms find protection and moisture while they await a ride home in the next high tide. The wrack can attract terrestrial bugs and their predators, and is critical for resident and migratory shorebirds for foraging[3]. Wrack can also catch sand that is swept by wind or waves across the beach, thereby helping to build beach and dune structure and contributing to storm protection[16].

Currently, wrack extent, condition and function are not tracked by any regulatory programs in Massachusetts, and this habitat is not specifically protected by regulation but does require approvals prior to removal and disposal from a beach[16]. The wrack line can overlap with other habitats listed above such as coastal beach, rocky intertidal and salt marsh.

In the Wetlands Protection Act Regulations, wrack is referred to as “storm drift”, which is deemed vital for local and migratory birds and serves an important role in nutrient recycling as organic matter breaks down. Still, wrack is often removed by manual and mechanical raking at many popular beaches to save beach-goers from encountering unsightly or foul-smelling detritus. There are currently no routine efforts to map wrack in

Massachusetts, however, the MassBays National Estuary Partnership has a citizen science project that logs plant and animal taxonomies found in the wrack[17].

2.1.6 Algae

Algae are plant-like organisms found in many forms in the nearshore marine environment, including at the micro or macro scale, attached to substrate or drifting planktonically, unicellular or multicellular, and comprising different pigments. Microalgae include phytoplankton such as diatoms, blue-green algae and dinoflagellates; while macroalgae include the green, brown and red seaweeds. As primary producers, algae in all forms play a critical role in the estuarine and marine food webs, while also creating structured three-dimensional habitat (in the case of macroalgae), producing oxygen as a byproduct of photosynthesis, and sequestering greenhouse gases[3].

Too much algae can be problematic, though – they can smother other lifeforms, reduce water clarity, or present risks to human health. Excessive nutrients coupled with warm water temperatures can lead to harmful algae blooms such as red tides, which can sicken beachgoers[2].

Because algae can exist in so many forms and in a variety of locations along the coastal gradient (e.g. attached to intertidal or subtidal rocks, washed up on shore, floating among eelgrass) it can present challenges in mapping. For the purposes of this project, only macroalgae (seaweeds) are considered. More specifically, algae attached to rocks are grouped into the rock class, algae within the wrack are included in wrack, and macroalgae that are drifting in the water column or atop submerged sand are identified as submerged algae.

2.1.7 Dunes

A coastal dune is a mound of sediment that is situated landward of the coastal beach, where sediment is deposited by storm over-wash and wind[6]. In Massachusetts, dunes are most prevalent on Cape Cod and the Islands thanks to an abundance of glacial moraine material, but are also found in several North Shore areas[3]. Dunes are significant to storm damage prevention, flooding control, and wildlife habitat[5]. At a higher elevation than the adjacent coastal beach, dunes provide a barrier between the sea and upland infrastructure. Storm and wind energy can lead to dunes eroding or accreting, or even shifting landward or seaward. The natural variability in dune volume and placement is critical to its function in flood control.

In terms of wildlife habitat, dunes are important nesting and foraging habitat for a variety of shorebirds like terns, gulls and plovers. Often but not always, dunes are vegetated, which further enhances their use by wildlife as well as aids in their stability and sediment retention. Common vegetation includes American Beachgrass (*Ammophila breviligulata*) and Beach Heather (*Hudsonia tomentosa*)[6].

Mapping of dune location is important as activities on and within 100 feet of coastal dunes are regulated[5]. For example, a residential home may not be constructed in the dune or its buffer if it affects the sand supply to or from the dune, alters vegetation, or interferes with the landward movement of the dune. The greatest threats to dunes are coastal construction and access-related destruction from vehicles and foot traffic[2].

2.2 Remote sensing to map coastal habitats

2.2.1 Around the world

Remote sensing of coastal ecosystems comes in many shapes and sizes around the globe. Multispectral imagery is used in land use assessments, thermal sensors are used to map sea surface temperatures, microwave radiometers inform ocean salinity and hydrological studies, LiDAR can produce bathymetric maps, and boat-based acoustic methods can map seafloor features – all of which can contribute to the generation of habitat maps and models[18]. And as remote sensors and data analysis techniques continue to advance and streamline, their use in coastal habitat mapping programs increases[19].

Satellite image classification, either through machine or manual methods, is a common tool for coastal wetlands inventorying even at the national scale. For example, the US Fish and Wildlife Service has been using satellite and aerial imagery to measure wetlands extent for several decades. Similarly, India has employed a satellite program to track mangroves, coral reefs, seagrasses and dunes across the country's coastline[20]. And while species identification can be problematic even in finer resolution satellite imagery, there have been great strides in recent years using hyperspectral imagery[18]. Mangrove, marsh and coral reef extents have all been tracked with satellite imagery[21,22,23]. Marshes and mangroves lend themselves to such mapping because they exist above the water at least some of the time, and coral reefs are able to be mapped remotely thanks to the clear tropical waters they inhabit. While many seagrasses exist in the same conditions, there are numerous species that exist subtidally in temperate, more turbid waters and can thus be more difficult to detect. Still, there are examples where seagrasses were successfully mapped with airborne imagery[24], satellite imagery[18,25,26], acoustic remote sensing[27,28,29] and various combinations of all three[26,28,29] across the globe.

The coupling of remote datasets is a common theme in habitat mapping. One study in Spain coupled airborne hyperspectral imagery and Light Detection and Ranging (LiDAR) data to map rocky shores and coastal wetlands, and found that incorporation of LiDAR greatly improved classification accuracy compared to hyperspectral imagery alone, especially in wetlands[30]. Coupling the data allowed for better discrimination of distinct intertidal communities which were prone to misclassification when using imagery alone. Similarly, LiDAR was found to improve coral reef mapping and condition assessments when coupled with drone imagery[31].

While drone use in coastal mapping and monitoring is in its infancy, numerous experiments have demonstrated their potential in identifying and mapping seagrasses[32,33,34,35,36], salt marshes[37,38], coastal dunes[53], bivalves in the rocky intertidal zone[39,40], coastal erosion[41], subtidal sediment and fish nursery habitats[42], coral reefs[31,43], marine debris[44], jellyfish biomass[45], and behaviors of dugong[46], sharks and rays[47]. Novel approaches are being tested that utilize fluid lensing to produce 3D images of coral reefs in clear waters, using drone imagery that incorporates water-transmitting wavelengths and wave-correcting algorithms[43]. In Portugal, drones were used to map shallow rocky seafloor where rock classes were differentiated into boulders, blocks and rock platforms[48]. The study incorporated SCUBA-based quadrat data about biological assemblages in each rock class, resulting in very high resolution mapping of both the hard-bottom habitat and the biota distribution associated with it.

In the US, the North Carolina Division of Marine Fisheries (NC DMF) recently added drones to their estuarine benthic habitat mapping program that inventories shallow estuarine populations of oysters, clams, scallops, and submerged vegetation. The program collects high resolution drone orthoimagery and employs a Heads-Up digitization technique in ArcGIS Pro to manually draw polygons around various habitat types. NC DMF found that the habitat acreage able to be mapped by a two person team in a single day increased 5900% compared to field-only *in situ* mapping without an aerial component[39].

Drones are increasingly present in US state environmental programs, including in Alaska, Arizona, Arkansas, Connecticut, Delaware, Kansas, Kentucky, Louisiana, Maryland, Michigan, Montana, New York, North Carolina, Oklahoma, South Carolina, Texas, West Virginia, Wisconsin and Wyoming[49]. While there is not a dedicated drone program in Massachusetts' Department of Environmental Protection (DEP) or sister agencies within the Executive Office of Energy and Environmental Affairs, the MA Department of Transportation has a drone program primary used for highway surveys, but that can be requested to assist other departments.

2.2.2 In Massachusetts

In Massachusetts, the DEP mapped wetlands on a state-wide scale with a fixed-wing manned aerial photography survey from the 1990s to early 2000s, and have since re-interpreted their data using more recent aerial photography in order to assess wetland changes[6]. DEP's Wetlands Conservancy Program (WCP) used color infrared sensors and stereoscope interpretation methods to identify freshwater wetlands, salt marshes, tidal flats, rocky shores, and sandy beaches at a scale of 1:12,000. The program used a minimum mapping unit

(MMU) of 0.25 acres, meaning habitat areas smaller than this size were not included in their maps. DEP identified the loss of 1,049 acres of freshwater wetlands in a 10 year period, and has used their maps to identify enforcement cases resulting in over $3Million in penalties and orders to restore nearly 70 acres of wetlands[6].

Within DEP's WCP is the Eelgrass Mapping Project (EMP)[14] which follows NOAA's Coastal Change Analysis Program protocols and captures imagery at a 1:20,000 scale to track changes to known eelgrass meadows, providing nearly coast-wide coverage approximately every five years. Other entities in Massachusetts conduct *ad hoc* mapping of coastal habitats, including eelgrass and other seafloor mapping via side scan sonar, underwater video and SCUBA divers by the Division of Marine Fisheries[29]; and MA CZM's programs that track shoreline change and erosion, salt marsh response to sea level rise, and marine sediment mapping. In addition, various academic and NGO endeavors use remote and field-based methods in salt marshes[50,51,52], coastal banks[41] and eelgrass beds[34,54,55]. These efforts exist because there is a need to fill in the spatial and temporal gaps in DEP's data to better track resource status, and to help elucidate patterns in habitat loss – especially in the case of salt marsh and eelgrass. Both habitat types have experienced substantial losses in Massachusetts since the onset of their respective mapping programs in the 1990s[6,14].

In the 5+ year period between DEP mapping efforts, a variety of chronic and/or acute impacts can significantly alter both salt marsh and eelgrass extent and quality. However, with more frequent high resolution mapping, the response of these habitats to stressors can be more readily detected, understood, and acted upon. Especially in the case of acute stressors, a drone survey method with low operating costs and high temporal and spatial resolution could help resource managers quickly assess sites of interest without incurring major costs to their programs. Such a drone method would complement, and not replace, existing mapping programs. In Massachusetts, some limited drone work has been conducted in salt marsh studies at the Plum Island Ecosystem Long Term Ecological Research (LTER) Network affiliated with the Marine Biological Laboratory, where imagery was coupled with LiDAR elevation to track extremely high resolution changes along a transect of salt marsh and adjacent shoreline[52]. Additionally, experimental drone-based eelgrass mapping has been conducted at MIT Sea Grant[34].

2.3 Drone technology

2.3.1 Types of drones

Drone technology and capability is ever-changing, though there are a limited number of basic drone types (Fig 2). Single rotor drones look and behave much like helicopters, and are called single rotor because they use only one primary rotor for creating vertical thrust, while a small tail rotor controls direction. Multi rotor drones have more than one rotor creating thrust, and common models have 3, 4, 6, 8 or more rotors. They have a large market and are relatively inexpensive to manufacture, which drives their consumer price down. Multi rotors are also relatively less complex and less difficult to operate than other types, making them very popular among professionals and hobbyists. Fixed wing drones look and behave much like airplanes, using the same principles of aerodynamics to generate lift and thrust. They can be used for far longer missions, but do not have the ability to hover in the air to collect imagery or other samples. Launching and landing can be more complicated as well, requiring a runway or other accommodations. Finally, many different hybrids designs exist that combine features of rotor and fixed wing drones.

Figure 2. Types of drones. Adapted from www.auav.com.au[56]

Types of drones are further defined by how they are powered (e.g. battery cells, fuel cells, airplane fuel, solar), the payload they can carry, their level of autonomy, and size. Joyce et al.[57] provide a great decision process in defining one's drone capability needs.

2.3.2 Flight applications

For flight planning and piloting in the field, there are numerous applications available that range in complexity, features and price. DroneDeploy and Pix4DCapture are two very popular and comprehensive applications, offering automated flight plans and robust post-flight processing including generation of orthomosaics and 3D products. They are compatible with DJI and many other consumer-grade drones, and their flight planning tools are free while image processing requires the purchase of a plan. Other applications include DJI GS Pro, Propeller Aero, Map Pilot, Litchi, PrecisionFlight, KittyHawk, and AirMap. These applications differ in their processing capabilities, integration of weather and airspace information, pricing, and user interface.

2.3.3 Best practices

Most recreational and commercial drone work falls under the FAA regulation 14 CFR Part 107 as "Small UAS Rule"[58]. Requirements when using any drone between 0.55 lbs and 55 lbs in weight include acquiring FAA licensure, registering the drone, flying no higher than 400 ft elevation, keeping the drone within line-of-sight, flying only during daylight, and avoiding restricted areas (e.g. airspace around an airport) unless granted approval. The rules are quickly changing as drones become more common in airspace, so the most important best practice when using a drone is to ensure compliance with regulations[58].

Flying a drone to collect high quality imagery over water is more complex than over land due in part to inherent risks of water, salt and sand exposure to equipment. Further, imagery collected to map underwater features can be rendered useless if waves, turbidity or solar glare prevent a clear view to the seafloor. If such features are not identifiable, mosaicking software may fail when trying to stitch images together. Thus, collecting imagery from a drone in the coastal zone requires a unique set of environmental conditions and logistical considerations in order to be successful[57]. In the last few years, various researchers have addressed best practices when using drones in the coastal zone[35,59], including methods to detect and map salt marshes[35,37,38] and different species of seagrasses[32,36]. Dobroski[60] details the many considerations in survey design, drone style, cost, and best practices in flight planning and image processing when working in salt marshes. Duffy et al.[59] provides flight planning considerations when flying in coastal areas, including conducting pre-flight compass and accelerometer calibration on stable ground before deploying from a boat, using landing pads when operating from a beach, cleaning parts with canned air after each flight, avoiding variable cloud cover, avoiding midday sun angle, and pointing the camera north to avoid solar glare. Nahirnick et al.[36] tested the effects of several environmental conditions (sun angle, tidal height, cloud cover, Secchi depth, and wind speed) and site characteristics (eelgrass patchiness and density, presence of other submerged vegetation, sediment tone, eelgrass deep edge and site exposure) on drone imagery over seagrass in British Columbia, Canada. The authors found that sun angle, visibility through the water column (a combination of tidal height, cloud cover and Secchi depth), and a combination of bed density (i.e. high percent cover) and continuity (i.e. not patchy) to be the most influential parameters on mapping confidence. Doukari et al.[35] found that classification of sub-optimal imagery resulted in differences in subtidal habitat acreage compared to those from optimal imagery of the same area at a seagrass bed in Greece. The presence of waves and sun glint in the sub-optimal imagery resulted in 10% less seagrass and changes to classified substrate types, compared to classifications of optimal imagery. Joyce et al.[57] provided general considerations specific to working over water, with a novel approach to planning a mid-day flight path, if unavoidable, where the drone is flying either directly towards or away from the sun azimuth to reduce glare. When slightly off-nadir photography was allowable, a 15˚ angle also helped to reduce glint while minimizing oblique distortions[57]. Optimal flight conditions described in the literature are summarized in Table 1.

Table 1. Optimal conditions for collecting aerial imagery of temperate and subtropical eelgrass via drone from Nahirnick et al. (2019)[a], Doukari et al. (2019)[b], and Joyce et al. (2018)[57]

VARIABLE	OPTIMAL CONDITIONS
SUN ANGLE	6.5-40˚ [a]; 25-45˚ [b]; < 35 ˚ [c]
WIND SPEED	< 8 km h^{-1} [a]; < 11.9 km h^{-1} [b]; < 9 km h^{-1} [c]
CLOUD COVER	0-10% or 90-100% [a]; < 25% [b]
PRECIP. PROBABILITY	< 50% [b]
TEMPERATURE	< 38˚C [b]
WAVE HEIGHT	≤ 0.5m [b]
EELGRASS MEADOW	Dense, continuous [a]
SAV MIXING	Sparse [a]
TIDAL STAGE	Low [a], Low-to-Normal if water clarity is good[b]
TURBIDITY	Low [a,c] (secchi depth > 5 m) [a]

Another way to improve image quality and accuracy is to deploy effective ground control points (GCPs). GCPs are markers set in the field that are visible in the aerial imagery, where precise location and elevation data are collected and used to enhance geographic rectifications and improve accuracy of image mosaicking. In the marine environment, setting GCPs can be challenging due to access and safety concerns[57]. Casella et al.[61] deployed colored underwater markers and scale bars when mapping coral reefs via drone in French Polynesia, where high water clarity allowed for visibility of underwater control points. Where water clarity does not allow visibility to the seafloor, floating ground control points with seafloor anchors are needed, necessitating a watercraft for deployment and retrieval. In their drone mapping program, NC DMF used sunken PVC pipes mounted with surface targets throughout their survey area and collected Global Positioning System (GPS) locations on each target[62].

Other best practices include using high imagery overlap settings (as much as 90%) to help mitigate issues caused by sun glint and to improve tie points (i.e. common detectable features) between images[57]. Additionally, battery life during a flight should never go below 25%, as low batteries tend to discharge at a faster rate, and wind can reduce battery life unexpectedly.

2.3.3 Imagery processing software

Numerous drone photogrammetry and processing tools abound, including proprietary Pix4D, eCognition, Agisoft PhotoScan, DroneDeploy, PrecisionHawk, Maps Made Easy, and others. These products feature workflows to correct imagery and generate mosaics (or orthomosaics, if spatial distortions are corrected), 3D models and a myriad of other outputs. In terms of ESRI products, three tools exist: Drone2Map, ArcGIS Pro Advanced Ortho Mapping, and ArcGIS Enterprise Ortho Maker tools. Choosing the right software for the job depends on the complexity of the workflow, volume of raster datasets, and desired outputs. Here, the ESRI products will be compared because this project aims to generate a repeatable workflow for organizations and agencies with ArcGIS and related tools in the ESRI suite.

Drone2Map for ArcGIS is a stand-alone application that does not require ArcGIS Desktop, Pro or Enterprise. It is relatively inexpensive, uses intuitive and very easy workflows, and can generate both 2D and 3D products including orthomosaics, point clouds, texture meshes, and digital elevation models (DEMs). Products are compatible with all ArcGIS mapping applications. As the name implies, it is specific to drone image processing. ArcGIS Pro Advanced has ortho mapping tools that also allow for creation of 2D orthomosaics and DEMs within the ArcGIS Desktop environment for a variety of imagery types including drone, satellite, and other aerials. Managing imagery in Pro is especially advantageous if working with large volumes of imagery. Processing can be automated using Model Builder or Python scripting; with the downside of Pro being its cost. Ortho Maker in ArcGIS Enterprise offers much of the same functionality as Pro, but supports multiple users in web-based workflows to process imagery. Enterprise can support the largest imagery collections, and products are shared automatically and rapidly across an organization. It is the most expensive of the ESRI products.

The three ESRI products listed above allow for easy publishing via ArcGIS Online. Pro and Enterprise have the added benefit of connecting to an ArcGIS Image Server to create dynamic image services.

Chapter 3. Research Methods

3.1 Site Selection

This study tests the efficacy of using an off-the-shelf consumer drone as a meso-scale mapping tool, for the purposes of enumerating habitat acreage and visualizing extent, within the gradient from upland beach to marine subtidal areas. DEP’s 2018 EMP and 2005 WCP maps were used to identify sites on the North Shore of Massachusetts that contained eelgrass in addition to at least five additional habitat types to achieve the desired habitat complexity. Additional habitat types included dunes, coastal beach, submerged sand, rocky intertidal, submerged rock, salt marsh, algae and wrack. Sites without public shoreline access or in controlled FAA airspace were avoided, and the FAA web and mobile app B4UFLY was used in airspace planning[63]. The site selection process identified Hodgkins Cove in Gloucester, Manchester Harbor in Manchester-by-the-Sea, and Mingo Beach in Beverly as suitable study sites (Fig 3). Launch location coordinates and the habitats present at each site are listed in Table 2.

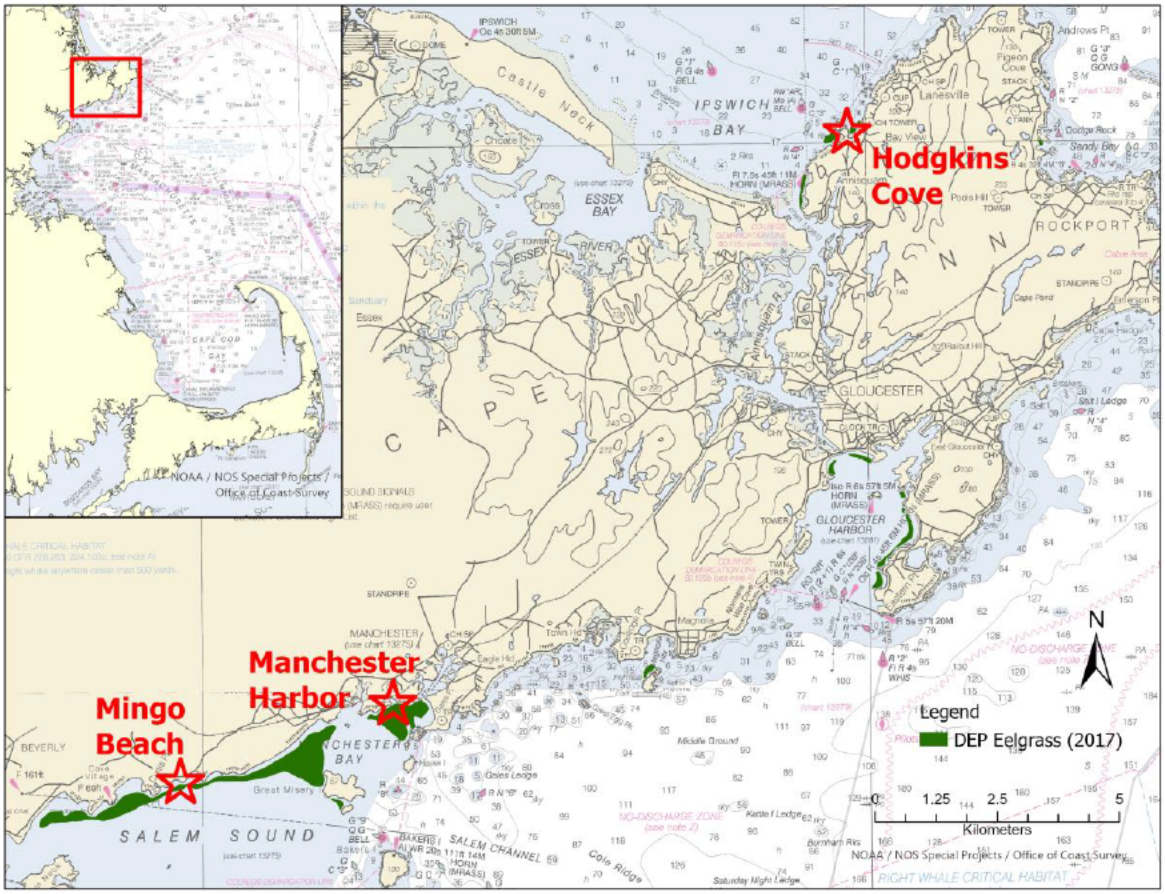

Figure 3. Study sites in northeastern Massachusetts

Table 2. Study site coordinates

Site Name	Street Address	Latitude	Longitude	Habitats
Hodgkins Cove	932 Washington St. Gloucester, MA	42.66933°	-70.66818°	Coastal Beach, Dunes, Rocky Intertidal, Salt Marsh, Eelgrass, Algae Submerged, Rock Submerged, Sand Submerged, Wrack
Manchester Harbor	75 Harbor St. Manchester-by-the-Sea, MA	42.56508°	-70.78669°	Coastal Beach, Rocky Intertidal, Salt Marsh, Eelgrass, Algae Submerged, Rock Submerged, Sand Submerged, Wrack
Mingo Beach	385 Hale St. Beverly, MA	42.55020°	-70.84021°	Coastal Beach, Rocky Intertidal, Eelgrass, Algae Submerged, Rock Submerged, Sand Submerged, Wrack

The Hodgkins Cove site includes a cove and an adjacent stretch of coastline on the northwestern shore of Cape Ann. The cove itself is sheltered by a natural low-lying rocky peninsula to the west and a man-made peninsula to the east. An adjacent stretch of shoreline containing salt marsh to the west of the rocky peninsula is included in the study site. The site also contains dunes, coastal beach, rocky intertidal and eelgrass habitat. Surrounding land uses include several residential properties, private beaches, and a small state university field station. The cove contains numerous boat moorings within the eelgrass meadow. Access to the field station driveway was granted by the property managers. Field groundtruthing was limited to what could be accomplished from walking across the beaches along the mean low water line, so as to not intrude on adjacent private residential property.

The Manchester Harbor site is a small protected cove near the outer harbor with moderate surrounding land uses including railroad tracks and forest to the north and several residential properties to the east and west. The cove is characterized by a sandy beach to the north that terminates at a man-made seawall, and extensive rocky shores to the east and west. Two small pocket salt marshes and a large continuous eelgrass meadow exist on the site, and the beach is frequently covered by an extensive mat of wrack (based on a review of Google Earth historic imagery). The eelgrass meadow at the site contains numerous boat moorings, and the harbor in general is heavily utilizes for recreational and commercial boating. Access to the site was gained by parking in a designated spot adjacent to the seawall.

Mingo Beach and the adjacent unnamed beach to the east are recesses along the Beverly coastline. Nearby land uses include several large university buildings, residential properties, and route 127. The site is characterized by a sandy-gravelly coastal beach bordered by extensive rocky intertidal, with eelgrass and the emergent Black Rock granite formation just offshore. Access to the site was gained by parking in a designated pull-off spot against the seawall along route 127.

3.2 Image capture

A DJI Phantom 4 Pro V2 quadcopter drone was selected as the survey platform due to its advanced 1-inch CMOS visible light RGB sensor (i.e. camera) which captures 20 megapixel color photographs and 4K video, has an optimized f/2.8 wide-angle lens with 84˚ field of view, user-friendly remote controller, and extended flight time (30 minutes) and speed capabilities (31 miles per hour (mph)). This drone can also resist movement in wind speeds up to 10 meters per second (22 mph). The camera is positioned using a 3-axis gimbal that can tilt the camera within a 120˚ range from direct nadir (downward, -90˚) view, to straight ahead (0˚), to an upward-looking angle up to 30˚ above horizontal. Imagery was collected with the camera in nadir orientation and the drone in Positioning-Mode (P-Mode) to optimize image georeferencing and mosaicking. Drone altitude was maintained using a built-in solid state pressure sensor (barometer) which measured altitude relative to the launch point. The drone was operated through the DJI remote console connected to an iPad tablet. FAA rules and regulations were followed at all times, and FAA Remote Pilot licensing was acquired prior to conducting flights.

Sites were flown during the summer growing season (June to September, 2020) and winter dormant season (December 2020 to January 2021) (Table 3). Targeted site conditions included flying within 30 minutes of a negative low tide, during low sun angle times of day (< 45˚), with < 5 mph winds, and cloud cover < 10% or > 90%. The sun angle condition was not adhered to in some instances where the desired tide stage and site access were limited to mid-day hours. The proprietary DroneDeploy application was used for flight planning and management, including automated route planning, launch, survey, and recovery. Flight altitude was set to 80 meters (m) or 90 m depending on site size and battery needs, with 75% front overlap and 65% side overlap of adjacent image tiles. At 90 m elevation, a 40 acre site was mapped in 10 minutes, with 165 still images at 1.1 inch (2.8 cm) per pixel resolution. At 80 m elevation, a 30 acre site was mapped in 14 minutes, with 229 images at 0.7 inch (1.8 cm) per pixel resolution.

Table 3. Flight dates and conditions.

Site	Date flown	Notes
Hodgkins Cove, Gloucester	6/28/2020	High solar glare due to flying too late in the morning. Could not do upland groundtruthing due to private property. Several boats on moorings and people on beach, but this is still the preferred dataset for analysis as it covers the entire site
	7/25/2020	Imagery was adequate for the cove proper, but had overexposure issues and poor data connection for the coastline and salt marsh area to the west
	1/10/2021	No issues, imagery adequate for analysis
Outer Harbor, Manchester	6/7/2020	Some slight glare and several boats on moorings, but imagery adequate for analysis
	12/13/2020	Late afternoon flight on cloudy day; low light levels resulting in slightly blurred imagery. However, still adequate for analysis because habitats are easily differentiated and water clarity was excellent
Mingo Beach, Beverly	9/6/2020	Some areas of minor glare, imagery adequate for analysis
	12/13/2020	Late afternoon flight on cloudy day; low light levels resulting in slightly blurred imagery. However, still adequate for analysis because habitats are easily differentiated and water clarity was excellent

All field imagery were managed within a file geodatabase in ArcGIS Pro and backed up on an external hard drive. For long-term data storage, imagery and all rasters produced during analysis will be kept on the hard drive indefinitely.

3.3 Groundtruthing

After each flight, groundtruthing in the upland portion of the site was conducted at 5-10 locations using the open source mobile application *My GPS Coordinates* (developer Andrew Neal, version 4.0), which allowed for geo-tagged photo-documentation of conditions along with information about the strength of the GPS signal and position accuracy. Images and waypoints (in WGS84) collected in the application can be exported to email as KMZ or GPX points, and used as-is in Google Earth (Fig 4), or converted into shapefiles for use in ArcGIS. Due to limited resources and lack of access to watercraft, subtidal areas at each site were not groundtruthed at the time of the flights. Rather, DEP's WCP and EMP map layers and previous SCUBA diving experience in the eelgrass meadows at each site informed the groundtruthing in these areas.

Figure 4. Example of groundtruthing data from Manchester Harbor (6/7/20). Data sources: cell phone photographs collected via My GPS Coordinates app, overlaid on Google Earth satellite imagery.

3.4 Image processing and analysis

3.4.1 Imagery manipulations and corrections

Image processing extracts useful information from digital images using computer algorithms, and is an essential part of image-based remote sensing. One form of processing is mosaicking, where individual images are stitched together in a way that seamlessly joins and color-balances image edges while geometrically correcting lens distortion and the perspective of the camera relative to objects in the image. Various softwares can perform this step by using embedded information about the camera's location, elevation, and field of view, along with matching objects (i.e. tie points) detected in overlapping adjacent images. Post-flight data processing was done using both DroneDeploy's orthomosaic tool (summer flights only due to expiration of trial plan) as well ESRI's Drone2Map software extension for ArcMap (all flights). The latter had the added benefit of generating additional 2D and 3D products like digital surface and terrain models. It should be noted that ArcGIS Pro has a dedicated drone imagery processing toolkit, which includes mosaicking, ground control integration, and other spectral and spatial rectifications. Pro's built-in mosaicking tool was experimentally tested with imagery from one study site, and found to produce a mosaic with more missing tiles and less colorimetric smoothness at image boundaries when using default settings compared to the same imagery processed using default settings in Drone2Map. For that reason, Drone2Map was used for all image mosaicking.

During mosaicking in Drone2Map, ground control points, if available, can be incorporated to improve horizontal accuracy. In lieu of collecting high resolution ground control points for this project, USGS Color Orthoimagery (2013/2014) was imported into Drone2Map to visually compare horizontal accuracy between drone and USGS orthoimagery. Extremely high agreement was observed, and therefore additional ground control manipulations were not carried out. However, it should be noted that absent true GCPs, it is possible for users to manually extract ground control points using features visible in high resolution orthoimagery by tying them to features in the drone imagery.

A frequent problem with drone image collection over water is the ability of the mosaicking software to detect tie points between individual image tiles over largely homogeneous open, featureless water. If an adequate number of tie points cannot be calculated, the image tile is dropped from the mosaic. It is possible to manually tie it back in, however, it is extremely time consuming, prone to user error, and requires additional processing to geographically correct for lens and perspective distortions. Use of ground control points is one mitigating measure, but it can be financially and logistically infeasible.

Mosaics created in Drone2Map were imported into ArcGIS Pro (version 2.7.1) in projected coordinate system WGS 1984 UTM Zone 19; and all work was done in this reference system. For each site, a clip polygon was created to facilitate removal of unwanted upland portions of the imagery (e.g. residential and wooded areas beyond the target habitats) and seaward areas of poor image coverage. The landward border of the clip polygon was traced along the 2005 DEP Wetlands Arc layer “shoreline” feature, or the so called “closure line” along the top of the coastal bluff or sea cliff features; whichever was located higher on the beach. The seaward border of the clip polygon traced the edge of either the summer or winter orthomosaic, whichever was more landward. Clipping the summer and winter imagery to identical extents allowed for comparison of habitat acreages between seasonal datasets.

3.4.2 Segmentation and classification

Image classification strategies can be grouped into different methods, including supervised and unsupervised, which refer to the use or disuse of known data points that train the classifier; and pixel-based or object-based, which refer to the individual pixels or groups of pixels being classified in an image. Object based image analysis (OBIA) classifies groups of spectrally- and spatially-similar pixels in an image. This differs from traditional pixel-based classifications which classify each pixel individually based on spectral properties alone. OBIA can greatly reduce the salt-and-pepper appearance of classification results, and offers a process that is more similar to what the human eye is capable of. For those reasons, it is becoming increasingly favored in the literature[64,65]. OBIA was a logical choice for this project, as the habitats of interest are spectrally unique and spatially continuous, lending themselves to being grouped into objects.

ArcGIS Pro offers two options for image segmentation: as the “Segmentation” tool in the Image Classification toolbox, and as a stand-alone spatial analyst Geoprocessing Tool, “Segment Mean Shift”. Both tools identify objects, features or segments in the imagery by grouping together adjacent pixels that have similar spatial and spectral properties. During experimentation, the two methods resulted in differing products because the Geoprocessing tool allows for setting both a minimum and maximum segment size (in pixels), while the Classification tool only allows for setting a minimum. This was problematic for very high resolution imagery over water because without a maximum segment size, all aquatic and beach areas were grouped together regardless of the spectral and spatial settings, while land features were segmented as desired. With the ability to set a segment maximum size, the Geoprocessing tool generated more logical and desired results, even though the behind-the-scenes processing is largely the same in each tool. Another shortcoming of segmentation of extremely high resolution imagery is the presence of a grid artifact in the output that seems to come and go as the raster goes through different processing steps. These segmentation issues could be due to the newness of the software and its individual processing tools, which are arguably aimed more for terrestrial uses than marine. Fortunately, ESRI developers actively request and acknowledge feedback from the user community to further revise the tools through their forum.

The optimal settings for spectral detail, spatial detail, and segment size minimum and maximum were determined by testing various combinations in the segmentation step of the Classification Wizard. In this step, the Wizard allows you to alter settings and preview the output prior to running the segmentation. The preview process need only be carried out once for an entire imagery set collected so long as the same flight specs were used and images are over similar landscapes. The spectral and spatial detail settings directly relate to segment smoothing, and segment size relates directly to the desired minimum and maximum mapping unit (in pixels). The spectral detail setting controls the level of importance or weight given to color differences between features in the imagery, with a unitless scale from 1.0 to 20.0. Lower values result in broader classes, more smoothing, and longer processing time. Higher values should be used when features have somewhat similar spectral characteristics but should be classified separately. For example, a higher value in forest imagery will better distinguish different tree species. The spatial detail setting has the same unitless scale, and sets the level of importance given to spatial proximity between features in the imagery. Again, lower values create broader classes and more smoothing. Higher values are useful when features of interest are small and tend to be clustered together. For example, in an agricultural scene, crops could be segmented apart from roads and trees using a smaller spatial detail value, or different crop types can be segmented from one another using a higher value. Minimum segment size relates to the MMU desired for analysis. Segments smaller than the selected size are merged with their best fitting neighbor segment. When a maximum segment size is set, any segments larger than the specified size will be divided. The optimal settings were found to be a spectral detail of 18.0, spatial detail of 12.0, minimum segment size of 100 px and maximum of 1,000 px. The Geoprocessing tool was ultimately chosen for image processing because by applying a maximum segment size, the very high resolution imagery was segmented into more logical segments in both upland and underwater areas.

Using the winter Mingo Beach imagery dataset, six classifiers were chosen for testing to determine the preferred classifier. Using the Image Classification tool, the Iterative self-organizing (Iso) Cluster, Support Vector Machine, Maximum Likelihood and Random Trees classifiers were tested in a variety of training and segmentation scenarios (Table 4).

Table 4. List of tested classifiers and their characteristics.

Classifier	Pixel or Object-Based	Supervised/Unsupervised
Iso Cluster*	Pixel	Unsupervised
Iso Cluster*	Object	Unsupervised
Support Vector Machine*	Pixel	Supervised
Support Vector Machine*	Object	Supervised
Maximum Likelihood*	Object	Supervised
Random Trees	Object	Supervised

A classification schema was created to establish possible classes that each pixel or object could be assigned to during classification. The new schema, "Coastal Habitats", closely matched the habitats identified by DEP's WCP, including four of the 28 wetland classes identified by DEP in the 2005 Wetlands dataset, as well as eelgrass from the DEP 2016 eelgrass dataset. Wrack and submerged algae were also included in the schema, though they are not target classes in any known mapping efforts (Table 5). Use of NOAA's C-CAP Regional Land Cover Classification Scheme[66] was considered, but classes would not correspond to DEP's and would have to be cross-walked as part of this project in order to provide comparisons with DEP's layers.

Table 5. Schema of classes created for classification with corresponding DEP class information.

COASTAL HABITATS SCHEMA CLASS	**DEP CLASS**	**DEP MAP PRODUCT**
Coastal Beach	Coastal Beach	DEP wetlands (2005)
Dunes	Coastal Dunes	DEP wetlands (2005)
Rocky Intertidal	Rocky Intertidal Shore	DEP wetlands (2005)
Salt Marsh	Salt Marsh	DEP wetlands (2005)
Eelgrass	Eelgrass	DEP Eelgrass Mapping Project (2016)
Algae Submerged	--	--
Rock Submerged	--	--
Sand Submerged	--	--
Wrack	--	--

Following image segmentation and schema development, the next step for supervised classifications was creation of training sites, which were created based on field groundtruthing data and points visually interpreted from DEP's WCP and EMP polygons. Separate training sites were established for summer and winter orthomosaics from each site to account for seasonal habitat variability. Training sites were drawn using the circle tool, but options are available for using individual points (pixels) or polygons. Circle size varied, but most training sites encompassed 25-100 or more pixels at a time. The total area of training sites per habitat class was at least 2% of the total size of each habitat class.

With segmentation, schema, and training steps complete, each segmented raster was run through the classifiers using the segments' mean digital number as the attribute on which the classification was based. Classification results were visually assessed, and additional training sites were iteratively added if problematic areas were observed. After determining the preferred classifier, the above steps were completed for all orthomosaics from from each site.

3.4.3 Accuracy assessment

Accuracy assessments were used to evaluate the performance of six different machine classification scenarios tested in the process of finding the right classifier (Table 4), as well as to evaluate classifications across all three sites after a preferred classifier was chosen. The first step was the creation of accuracy assessment points, which were reference points of known classes that were compared to the classified results. There are several ways to go about this step: points can be extracted from an existing classified raster, extracted from existing polygons, or manually created as a point layer. Because DEP wetland and eelgrass layers are of much coarser resolution than the classification results, I opted to manually create accuracy assessment points informed by visual interpretation of those layers, the drone imagery, groundtruthing points, and several secondary datasets including eelgrass polygons resulting from DMF's side scan sonar survey in Salem Sound (2016), consultant eelgrass surveys in Hodgkins Cove provided by DMF (survey performed 2018), and DEP's field groundtruthing historic subtidal eelgrass presence/absence point data from the EMP. Points used to train the classifiers were not used for accuracy assessment, and point selection was done blindly from classified and segmented rasters. One set of accuracy assessment points (n=300) was made for each seasonal orthoimage at each site.

Points were created using the "Create Accuracy Assessment Points" geoprocessing tool, which used the classified raster to generate points in each class in a stratified random assignment, such that the total number of points was approximately 300 for the entire raster and each class had a proportional assignment of points. Points were then manually classified in the attribute table in batches, selecting areas of same-class points and calculating the automatically-generated “GrndTruth” field with the appropriate expression (e.g. GrndTruth = 40, where 40 is the class code for Eelgrass). Accuracy at each point was then computed graphically using the “Compute Confusion Matrix” tool, and matrices were exported to excel tables.

3.4.4 Change detection

With summer and winter classified rasters clipped to the same extent, the area of each class present in the raster could be calculated and compared across seasons. The attribute table for each raster was edited to include a calculation of the habitat class area by first using the Build Raster Attribute Table tool, adding the pixel count per class to the attribute table, then multiplying the pixel count by the source imagery pixel size (e.g. 0.0251999 m^2) to achieve area in square meters for each class; and finally converting to acres (where 1 ac = 4046.86 m^2).

To create a visual assessment of the geography of habitat changes, the Compute Change Raster geoprocessing tool within the Change Detection Wizard was used to generate a new raster showing only the pixels where a categorical habitat class change occurred between summer and winter imagery. In the generated output, each change-type is symbolized differently, and areas of no change omitted. Settings used were computing change based on categorical difference, but other options are available including basing change off pixel value (useful for continuous data like temperature) or time series change (useful for identifying at what date a change occurred within a time series of imagery). Classes can be interactively selected for change analysis to target the analysis to specific “change from” and/or “change to” fields, but all possible class changes were kept for this assessment.

To summarize the processing and analysis steps listed throughout chapter 3.4, a workflow diagram was developed, where key tasks (Compile Datasets, Data Pre-processing, Classification, Change Detection, and Accuracy Assessment) are detailed with specific steps, softwares and tools (Fig 5).

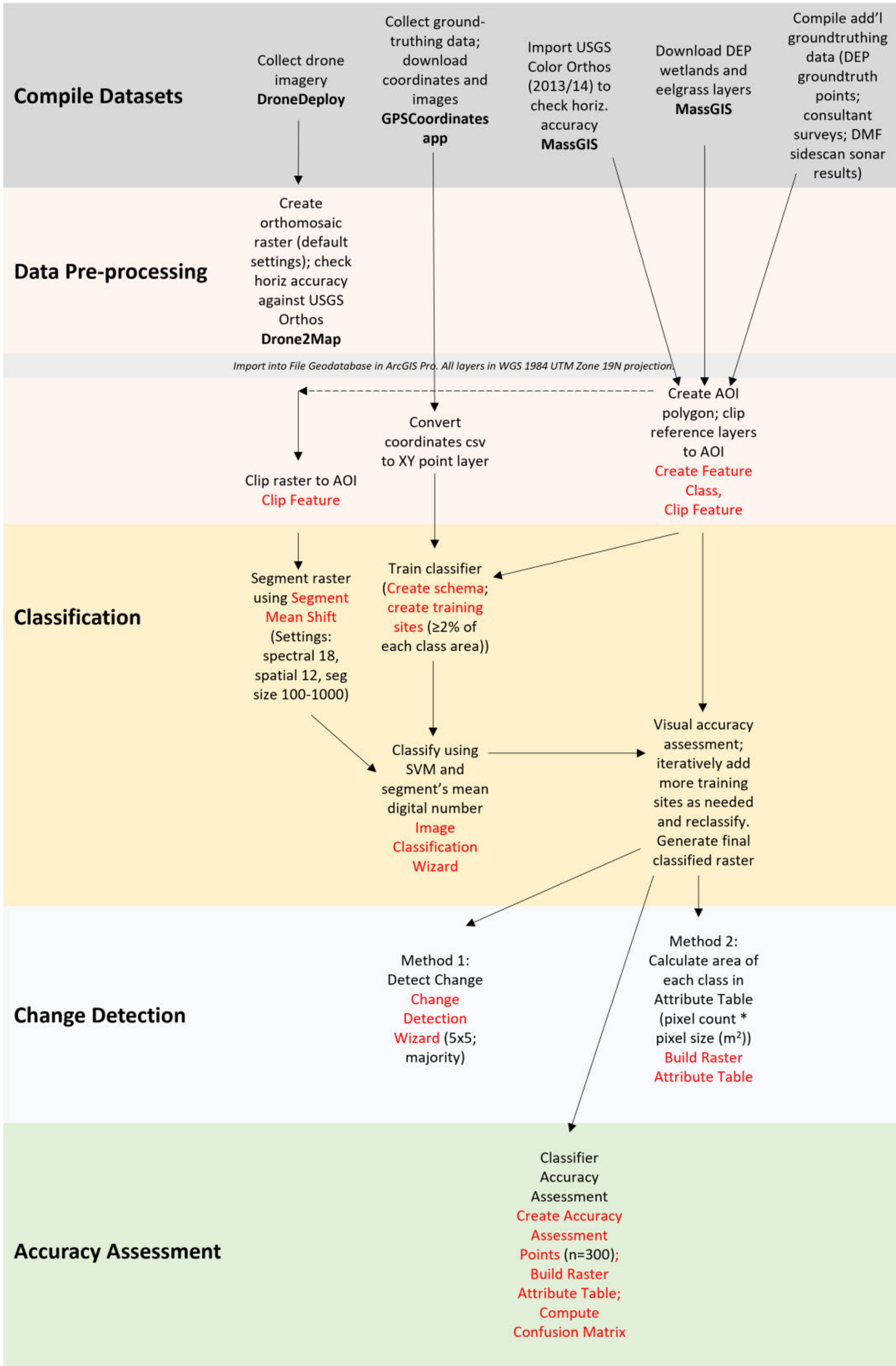

Figure 5. Workflow for the processing and machine classification of drone imagery for coastal habitat mapping. Software and applications are shown in bold; if unspecified, software was ArcGIS Pro. Specific tools used in each step are in red.

3.4.5 Comparison with Manual Delineation

One of the primary research questions of this thesis is if drone imagery can effectively supplement existing mapping programs. In Massachusetts, the WCP and EMP conduct their work at far coarser temporal and spatial scales, and the level of detail provided by sub-meter machine classification may be overkill for the state-wide scale of mapping work being performed. To test the efficacy of drone imagery as an alternate imagery source for programs that monitor salt marshes and eelgrass meadows, these habitats were manually delineated for each season at each site using a Heads-Up digitization process, so named because the focus of the user is up on the screen as they digitally trace features on a map or image. Only vegetated habitats were mapped with this method due to time constraints.

Used by many others in image analysis, and specifically by those who process coastal drone imagery for statewide resource mapping (e.g. NC DMF), Heads-Up allows for faster processing, integration of more user information and context about a site that may not be easily transferrable into training or reference layers, and allows the use of logic to deal with issues around glare, shadows, and dropped pixels. Heads-Up digitization can be performed at many scales, such as at the source scale (~2.5cm^2) or at a coarser, harbor-wide scale. To reach a balance of useful level of detail and effort required, a scale of 1:1,000 was decidedly a reasonable scale at which to work during manual delineation. While panning the orthoimage at that scale, and taking groundtruthing and reference datasets into account, a polygon was drawn along the visible edge of salt marshes and eelgrass meadows. Individual patches or bare areas within a larger polygon of a single habitat-type were not partitioned out.

Chapter 4. Results

4.1 Image quality and usability

The DJI Phantom Pro V2 successfully collected high resolution nadir imagery over the study sites (Fig 6). Image quality for mapping use was best when the optimal flight conditions were met (Table 1). When conditions were sub-optimal, such as sun angle > 45˚ or late afternoon dense cloud cover, the results were glare on the water surface and less crisp imagery, respectively. For the most part, image tiles were successfully mosaicked using Drone2Map, which outperformed ArcGIS Pro mosaicking in terms of colorimetric balancing and tie point generation (specifically over water), but underperformed DroneDeploy in terms of tie point generation over water (Fig 6). While DroneDeploy orthomosaics were able to incorporate more image tiles than Drone2Map, the cost of DroneDeploy's plans were a barrier to using their tools beyond the trial period.

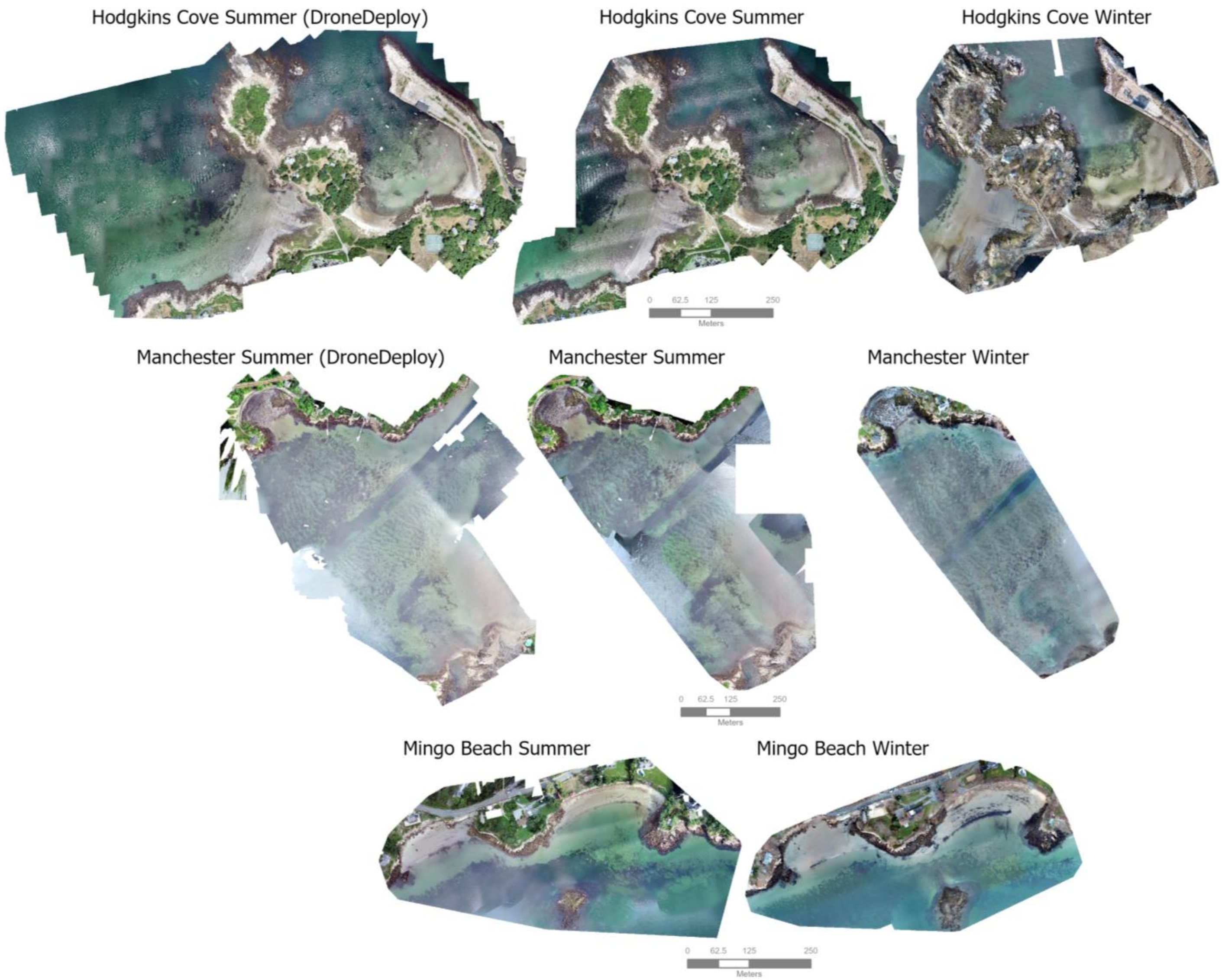

Figure 6. Orthomosaic results for summer and winter imagery at three study sites using Drone2Map and DroneDeploy (for Hodgkins Cove and Manchester summer imagery only).

In upland areas, no limitations on imaging capability were encountered, but subtidal areas were more problematic. The deep edge of the eelgrass meadow was able to be detected at least partially at all sites. The geography, depth and shape of the chosen study sites were conducive to successful mosaicking of imagery over water because of the juxtaposition of landforms and visibility of features on the seafloor that allowed for more successful tie point generation. Although the study areas' coastal waters were expected to have greater clarity in the winter than in the summer, summer and winter imagery were equally adequate for habitat mapping, with no substantial improvements in winter imagery (Fig 6).

4.2 Finding the Right Classifier

Six different classifier scenarios were tested using Mingo Beach summer imagery as a common dataset. The results of these tests have both subtle and obvious differences (Fig 7). Based on visual review, Iso Cluster classification scenarios often misclassified eelgrass, wrack, and both submerged and intertidal rocks – likely due to the untrained nature of this classifier. The unsegmented Iso Cluster had very fuzzy class boundaries, especially in subtidal areas. Segmentation slightly improved Iso Cluster results for subtidal areas but worsened results in upland areas, especially overestimating coastal beach. Maximum Liklihood and unsegmented Support Vector Machine frequently misclassified intertidal rocks as wrack, and Random Trees occassionally misclassified eelgrass as submerged rock in a spotty, peppered pattern. Visually, the segmented Support Vector Machine (SVM) results appeared most accurate based on known site conditions.

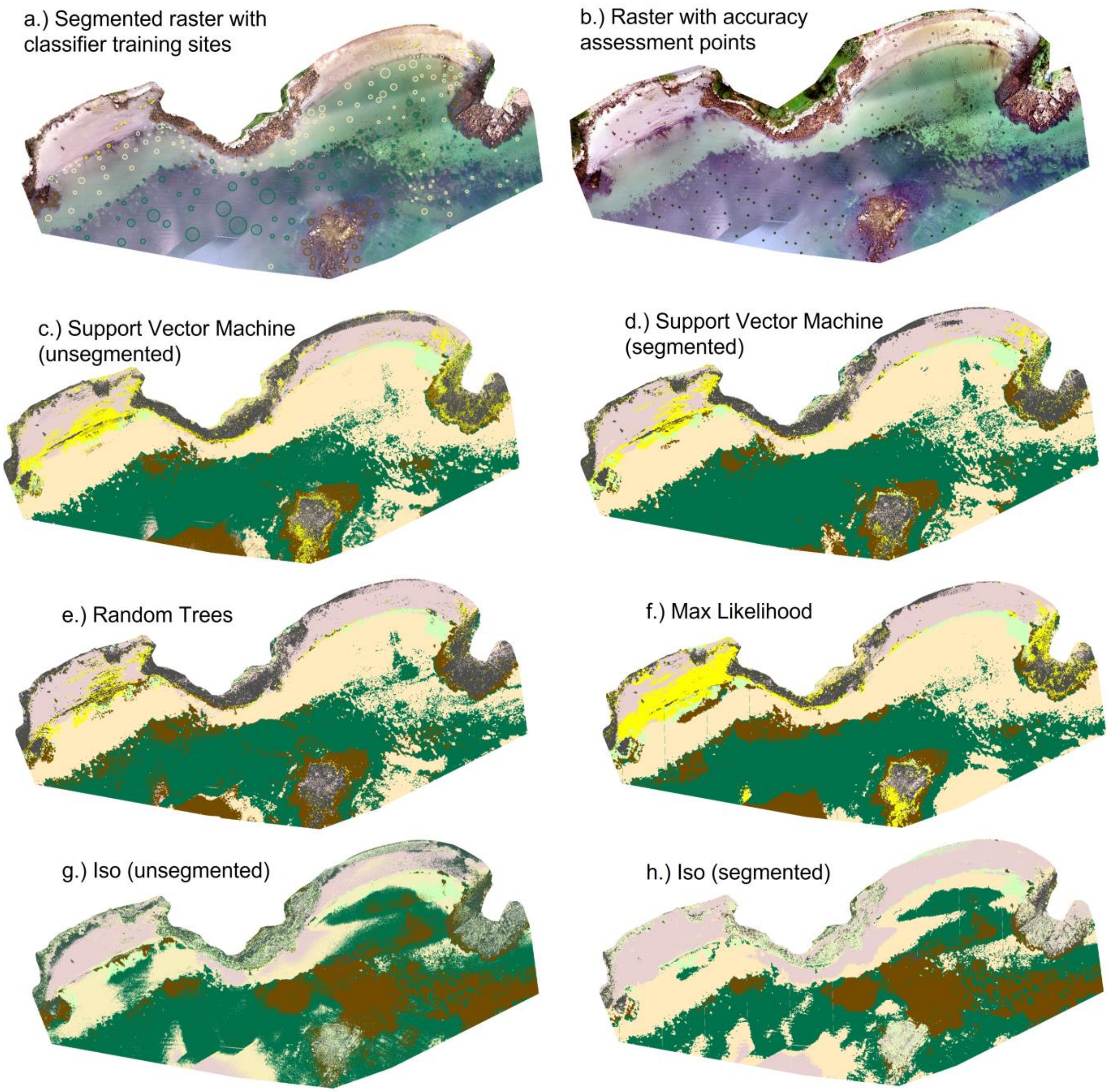

Figure 7. Training sites (a), accuracy assessment sites (b); and results of six classification scenarios (c-h) for Mingo Beach summer imagery.

Quantitatively, classification performance based on machine accuracy assessment of each classified raster is summarized in Table 6. Performance closely aligned with the visual interpretation of the results described above. The Support Vector Machine classifier had the highest overall accuracy and kappa values (79.4% and 72.8%, respectively), and performed better when run on a segmented raster than when based on pixels alone. Iso Cluster classifiers performed the poorest, though use of segmentation slightly improved results (Table 6). The overall accuracy and kappa values shown here lump all habitat classes together, though accuracies in individual classes varied greatly.

Table 6. Accuracy assessment results for 6 classifier scenarios as tested on Mingo Beach summer imagery, from best to worst performance.

Classifier	Pixel or Object-Based	Supervised/ Unsupervised	Total Accuracy (%)	Kappa (%)
Support Vector Machine	Object	Supervised	79.4	72.8
Support Vector Machine	Pixel	Supervised	76.4	69.1
Random Trees	Object	Supervised	75.7	68.5
Maximum Likelihood	Object	Supervised	71.4	63.2
Iso Cluster	Object	Unsupervised	52.5	39.5
Iso Cluster	Pixel	Unsupervised	49.2	35.1

The confusion matrix for the preferred SVM classifier is shown in Table 7. The orange-highlighted diagonal values indicate the number of accuracy points that were classified correctly for each class. User's and Producer's accuracies are measures of classification performance, where 100% accuracy indicates no misclassifications among assessment points. User's accuracy indicates the presence of false positives (i.e. errors of commission or overestimation), or locations where pixels were incorrectly classified as a known class but should have been identified as a different class. For example, where the classified raster indicated a pixel is coastal beach but the groundtruthing determined it is rocky intertidal. In this scenario, the coastal beach class had more pixels (which were false positives) than it should have according to groundtruthing data. These pixels are represented across the rows in Table 7. Conversely, Producer's accuracy indicates the presence of false negatives (i.e. errors of omission or underestimation), where pixels of a known class are left out, or omitted, from the appropriate class. In the same scenario above, the rocky intertidal class was missing pixels (which were false negatives) that it should have had. These pixels are represented in the columns of Table 7.

Table 7. Confusion matrix for the chosen classifier, segmented SVM.

		Reference									
		Coastal Beach	Eelgrass	Rock Intertidal	Wrack	Rock Submerged	Sand Submerged	Algae	Total	U_Accuracy	Kappa
Classified	Coastal Beach	25	0	7	2	0	2	0	36	69.4%	0
	Eelgrass	1	94	1	0	6	3	0	105	89.5%	0
	Rocky Intertidal	3	0	27	0	0	0	0	30	90.0%	0
	Wrack	5	0	1	2	2	1	0	11	18.2%	0
	Rock Submerged	0	6	0	0	12	0	2	20	60.0%	0
	Sand Submerged	0	13	0	0	0	74	2	89	83.1%	0
	Algae	1	0	2	0	2	0	5	10	50.0%	0
	Total	35	113	38	4	22	80	9	301	0.0%	0
	P_Accuracy	71.4%	83.2%	71.1%	50.0%	54.5%	92.5%	55.6%	0.0%	79.4%	0
	Kappa	0	0	0	0	0	0	0	0	0	72.8%

The Total Accuracy (79.4%), shown in blue where user (U) and producer (P) accuracies intersect, is a calculation of the total number of correctly classified pixels (i.e. the diagonals) divided by the total number of assessment points. The kappa index of agreement in the lower right corner reflects the difference between actual agreement and the agreement expected by chance alone. The actual, or observed, agreement is taken from the diagonal, while the chance agreement incorporates off-diagonal values. In the case of Table 7, the kappa revealed that the SVM classifier was 72.8% better than a random, chance-based assignment of assessment points to various classes. Kappa can be useful in comparing confusion matrices against one another when considering severity of misclassification. However, it should be noted that there is a recent push to remove kappa from accuracy assessments, as chance is argued to be irrelevant to accuracy assessment, and kappa values can be strongly influenced by the relative prevalence of classes[67].

In terms of individual class accuracies for the SVM classifier, of the seven habitats present in the Mingo Beach imagery, User's accuracy for eelgrass and rocky intertidal were very high (89.5%, 90.0% respectively), but very low for Wrack (18.2%) and Algae (50.0%). Wrack and algae are the two least common habitats on the site, occurring in a very spotty nature and always atop other habitat types (e.g. coastal beach, submerged sand) which may explain their poor accuracies. Still, the segmented SVM classifier outperformed all others tested, and was therefore run on the summer and winter orthomosaics for each study site.

4.3 Classification Results at All Sites

4.3.1 Segmentation

The segmentation process had better results in some areas than others. In the uplands and extremely shallow subtidal zone, segments were generated as intended. However, where water clarity and underwater feature visibility began to diminish deeper into subtidal areas, segments were more often created as individual pixels rather than smoothed objects (Fig 8). The size of the generated pixels in subtidal areas was directly related to the minimum segment size setting used in the segmentation tool, or 100 x 100 pixels in this case. The result was effectively a resampling of subtidal pixels into larger pixels - an unanticipated outcome.

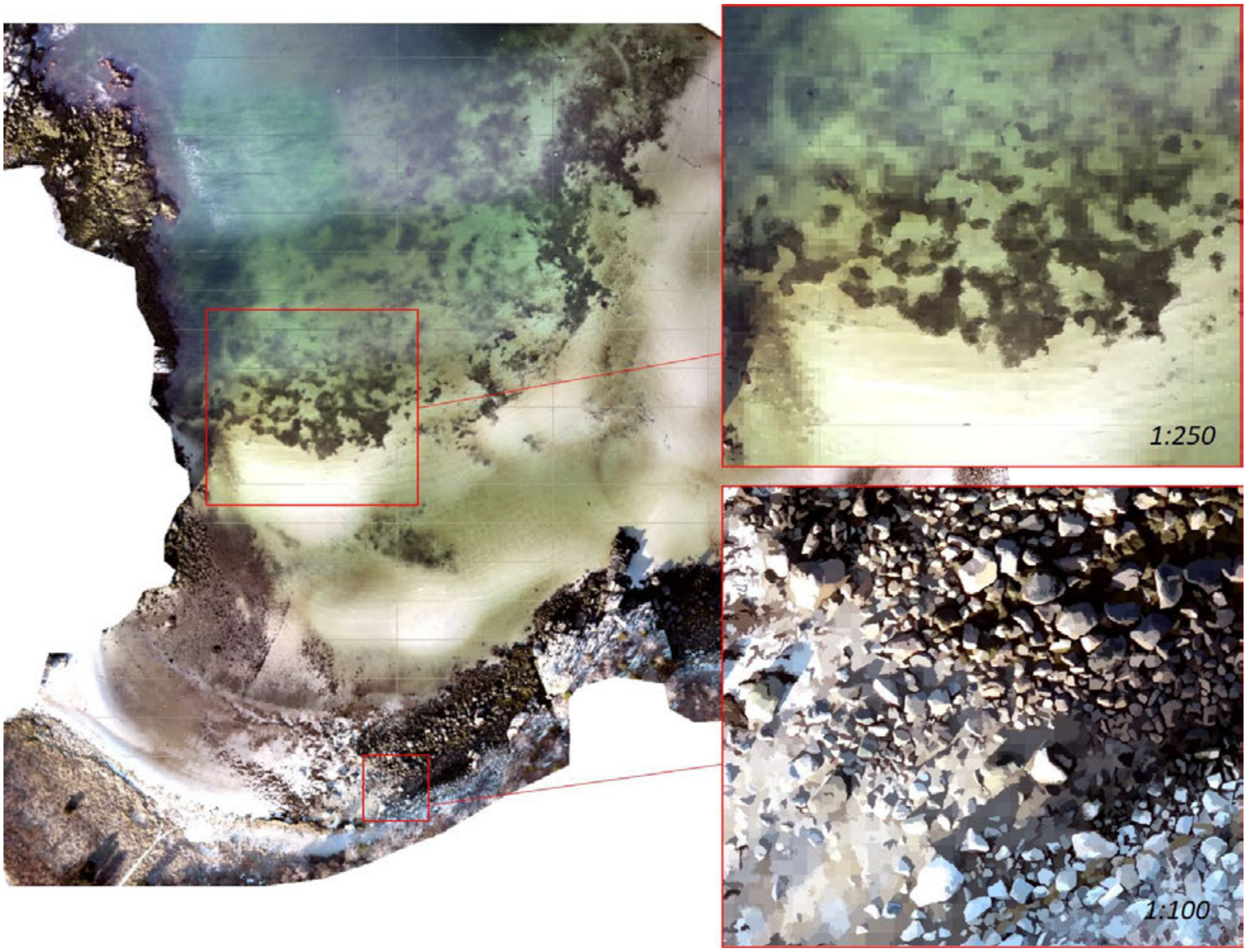

Figure 8. Different segmentation characteristics in the shallow subtidal eelgrass edge (top right) and in the uplands where beach and rocky intertidal exist (bottom right) at Hodgkins Cove. Imagery date 01/10/21.

Because the drone imagery was extremely high resolution, the resulting segmented rasters also had a very high level of detail, much more than anticipated at the start of the study. This high level of detail directly related to processing time - The Segment Mean Shift tool required roughly 1.5 hours of run time per mosaic.

4.3.2 Habitat classification

Classified rasters were successfully generated for summer and winter mosaics at each study site using the SVM classifier on segmented rasters (Fig 9). The results provide an extremely high level of detail about the location and extent of each habitat class. Habitat continuity and patchiness are also apparent, which is especially useful in visualizing where continuous, high density eelgrass areas transition to more patchy low density areas.

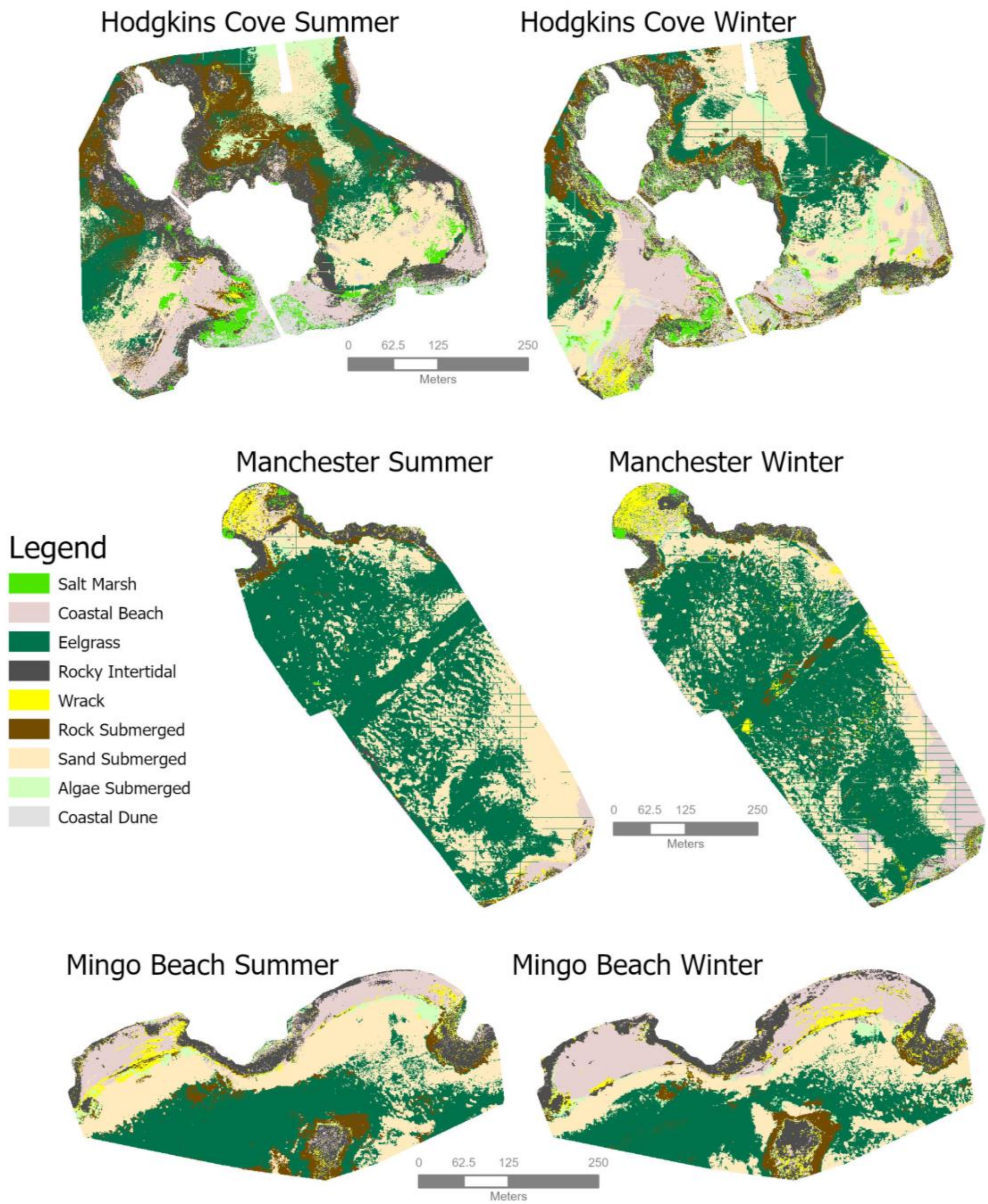

Figure 9. Classified summer and winter rasters for each study site

Some obvious misclassifications are apparent. At Hodgkins Cove, salt marsh was especially problematic, and errors of commission (overestimation) abound where classified salt marsh should have been sand, rocky intertidal, dune, or algae. Submerged rocks were also challenging here, with a substantial disparity between summer and winter imagery in a habitat class that was unlikely to vary temporally. Manchester and Mingo Beach had fewer obvious errors, however at all sites the rocky intertidal class was often peppered with errors of commission from several vegetative classes. The macroalgae that live atop rocky intertidal appear to have similar spectral characteristics to wrack material, salt marsh vegetation, and submerged algae; though rocky intertidal was very rarely misclassified as eelgrass.

In terms of computing time, running the classification itself was quite fast (< 10 minutes per mosaic), but the assignment of training sites was very time consuming (about 2 hours per mosaic). Training sites had to be added iteratively to achieve the best possible classification result which added to processing time.

4.3.3 Accuracy assessment

Classifier accuracy, and thus performance, greatly varied by habitat class (Table 8). Across all study sites, classification consistently performed well for eelgrass and rocky intertidal habitats, with mean accuracies of 85.3% and 81.0%, respectively. Mean accuracies were consistently low for salt marsh (30.3%), dunes (31.0%), wrack (39.5%), and submerged algae (20.0%); and moderate for coastal beach (68%), submerged rock (57.9%) and submerged sand (69.4%).

Classifier accuracy also varied by site (Table 8). Hodgkins Cove consistently had the lowest total accuracies, at around 59% for both summer and winter imagery, and accuracy was surprisingly low among all habitat classes. Manchester and Mingo Beach had higher total accuracy (80.2% and 79.4% for summer imagery, respectively) and were especially conducive to very high accuracies for eelgrass and rocky intertidal habitats. Season did not appreciably affect classifier accuracy at any site. The kappa values, which fold in the effect of random chance, are lower than total accuracies for each site and at each season. However, Mingo Beach kappa values are the highest of all the sites, and are closer to the total accuracy values.

Table 8. Accuracy and kappa values summarized from confusion matrices for all six imagery datasets.

		User Accuracy									User + Producer	
		Salt Marsh	Coastal Beach	Eelgrass	Dune	Rocky Intertidal	Wrack	Rock Submerged	Sand Submerged	Algae Submerged	Total Accuracy	Kappa
Hodgkins	summer	15.4%	55.3%	63.0%	50.0%	66.1%	50.0%	67.4%	69.6%	0.0%	59.3%	51.1%
	winter	18.2%	70.3%	73.7%	12.0%	80.0%	54.5%	56.0%	66.2%	10.0%	58.4%	50.4%
Manchester	summer	37.5%	60.0%	94.0%	NA	69.2%	70.0%	50.0%	73.2%	30.0%	80.2%	68.5%
	winter	50.0%	76.2%	95.3%	NA	92.3%	33.3%	30.0%	54.8%	10.0%	76.1%	60.8%
Mingo	summer	NA	69.4%	89.5%	NA	90.0%	18.2%	60.0%	83.1%	50.0%	79.4%	72.8%
	winter	NA	77.0%	96.5%	NA	88.6%	11.1%	84.2%	69.4%	20.0%	79.1%	73.5%
Mean		*30.3%*	*68.0%*	*85.3%*	*31.0%*	*81.0%*	*39.5%*	*57.9%*	*69.4%*	*20.0%*	*72.1%*	*62.9%*

It is difficult to interpret if these accuracies are in line with the literature as others have studied a myriad of habitats, water clarity conditions, processing softwares and classifier settings. However, for seagrasses, accuracies of 85-95% have been documented using drone imagery[35,68]; and Wicaksono et al.[69] found 75-88% total accuracy classifying coral, macroalgae, seagrass, rubble and sand testing several different classifier scenarios using satellite imagery. A study in the tropics found 81% accuracy classifying coral, mangroves, seagrass and sand using drone imagery; they also found that increasing flight elevation decreased accuracy, with peak performance at 75 m flight elevation[70].

Regarding kappa, classification performance can be categorized as poor (≤0%), slight (1-20%), fair (21-40%), moderate (41-60%), substantial (61-80%) and almost perfect (≥81%)[70], placing the present study's mean kappa score in the substantial category and the individual orthomosaic scores in the moderate and substantial categories.

4.3.4 Manual delineation

Heads-Up delineation resulted in the detection of measurable but minor seasonal habitat acreage changes, with < 3% difference between summer and winter acreage for both salt marsh and eelgrass (with the exception of a 9.5% difference in eelgrass acreage at Hodgkins Cove)(Table 9). There was a moderate degree of agreement between habitat acreage derived from the Heads-Up approach using drone imagery and the most recent DEP acreages that used Heads-Up on coarser resolution aerial imagery. For eelgrass, interpretation of drone imagery produced consistently higher acreage estimates compared to DEP, with differences primarily along lower-density shallow edge areas (Fig 10). Salt marsh was only mapped by DEP at one of the study sites (Hodgkins), where there was a 12% difference between drone-derived acreage and DEP acreage. Given that DEP's estimate was from 2005, these results may indicate this salt marsh is relatively stable.

There was also moderate agreement between acreages derived from Heads-Up and those derived from SVM classification, with Heads-Up again producing higher eelgrass estimates likely caused by the lumping in of lower-density edges and patchy, mackerel-patterned parts of the meadow (Fig 11). Salt Marsh acreages derived from Heads-Up were lower than those from SVM classification, likely attributed to poor machine classification accuracy for salt marsh as described in 4.3.3 above. With a clear trade-off between processing time and level of mapping detail provided at the scale of 1:1,000, Heads-Up delineations took less than 20 minutes to complete per raster.

Table 9. Vegetated habitat acreages derived from Heads-Up, Support Vector Machine, and DEP aerial surveys.

		Eelgrass (acres)			Salt Marsh (acres)		
Site	Season	Heads-Up	SVM	DEP (2016)	Heads-Up	SVM	DEP (2005)
Hodgkins	summer	9.85	6.46	6.37	0.95	1.82	1.07
	winter	8.96	7.47	NA	0.93	1.44	NA
Manchester	summer	42.95	31.29	39.02	0.14	0.19	NA
	winter	43.6	31.72	NA	0.14	0.21	NA
Mingo	summer	13.15	9.39	10.23	NA	NA	NA
	winter	12.75	8.69	NA	NA	NA	NA

Figure 10. 2015-2017 DEP eelgrass polygons (clipped to study areas) and drone-derived summer eelgrass extent overlaid on USGS imagery.

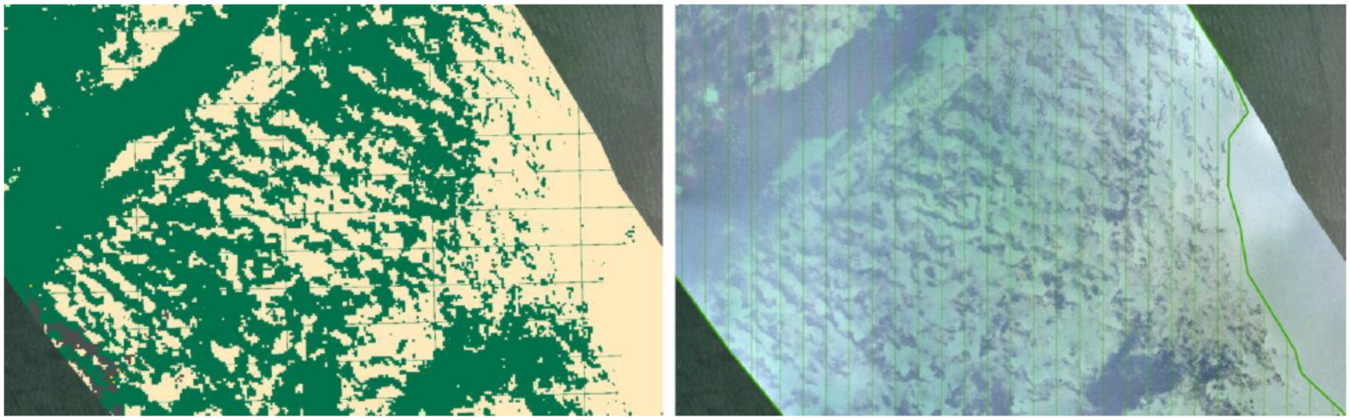

Figure 11. Area of mackerel-pattern eelgrass in Manchester outer harbor. Bands of eelgrass are individually mapped in the SVM classifier result (left, eelgrass in green) but lumped together in Heads-Up result (right, eelgrass in green hatch)

4.3.5 Change detection

Temporal changes in habitat extent and acreage between summer and winter imagery were able to be detected at a very fine scale using machine classification, and detected at a coarser scale using a Heads-Up delineation. Habitat acreages for each site and season as estimated by the SVM classifier are shown in Table 10. Often there was strong agreement in habitat acreages between seasons. At Mingo Beach, the magnitude of seasonal differences ranged from 0.00 acres of change (e.g. wrack) to 2.00 acres of change (coastal beach). The "gain" of coastal beach in the winter is attributable to minor changes in tidal stage at the time of flight, which can be confirmed by the "loss" of 1.42 ac of submerged sand. The same can be assumed for submerged and intertidal rocks. Eelgrass is more likely to be a true seasonal change, with a loss of 0.70 ac by winter. At Hodgkins Cove, the magnitude of seasonal differences ranged from 0.47 ac (salt marsh) to 2.96 ac (rocky intertidal), with an eelgrass gain of 1.47 ac in the winter. However, image quality and misclassification issues at this site may be more to blame than true acreage changes. At Manchester, the magnitude of seasonal differences ranged from 0.02 ac (salt marsh, submerged rock) to 4.62 ac (submerged sand). The "loss" of submerged sand is likely due to minor tidal changes, as well as an increase in winter wrack (1.23 ac) and submerged algae (0.32 ac). Eelgrass and salt marsh experienced 0.42 ac and 0.02 ac of winter gains, respectively.

Table 10. Acres of SVM-classified habitat by site and season, where a negative difference indicates a loss and positive difference indicates a gain between summer and winter.

	MINGO (acres)			HODGKINS COVE (acres)			MANCHESTER (acres)		
Habitat Class	Summer	Winter	Difference	Summer	Winter	Difference	Summer	Winter	Difference
Algae Submerged	0.80	0.71	-0.09	1.53	2.70	1.17	0.59	0.91	0.32
Coastal Beach	3.51	5.51	2.00	5.01	4.77	-0.24	1.24	4.02	2.78
Coastal Dune	0.00	0.00	0.00	1.55	3.38	1.82	0.00	0.00	0.00
Eelgrass	9.39	8.69	-0.70	6.46	7.47	1.01	31.29	31.72	0.42
Rock Submerged	2.21	1.46	-0.75	5.69	3.24	-2.45	1.04	1.02	-0.02
Rocky Intertidal	2.85	3.81	0.96	7.81	4.76	-3.05	2.51	2.38	-0.13
Salt Marsh	0.00	0.00	0.00	1.82	1.44	-0.38	0.19	0.21	0.02
Sand Submerged	8.39	6.97	-1.42	9.02	9.99	0.98	18.24	13.62	-4.62
Wrack	1.08	1.08	0.00	0.29	1.43	1.14	1.06	2.30	1.23
Total	*28.23*	*28.23*	*0.00*	*39.17*	*39.17*	*0.00*	*56.17*	*56.17*	*0.00*

Further, a highly detailed, pixel-by-pixel change analysis graphic was generated for each site showing where habitat class changed from summer to winter, broken down by each possible type of change (Fig 12). With so many change categories in the legend it is difficult to interpret these graphics aside from obvious problematic areas, however areas of no change (white) are quite clear.

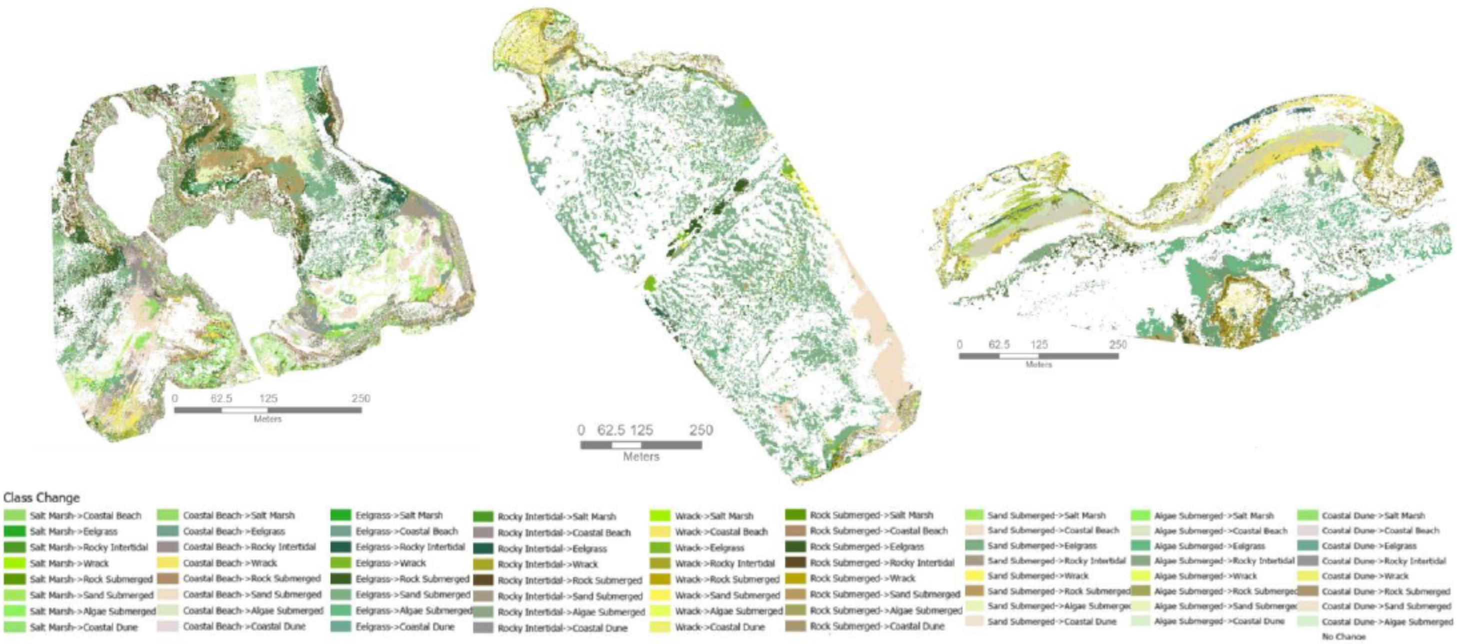

Figure 12. Geospatial habitat class change detection from summer to winter, showing pixels where change occurred, and categorizing the change based on starting and ending habitat class.

Histograms derived from the change detection maps (Fig 12) were used to rank the change categories by size, in acres changed per category. While the majority of change categories were responsible for < 0.25 ac of habitat change, some were more substantial. The top ten change categories from each site are in Table 11. While some of the leading changes were most likely from classification error related to tide stage inconsistencies (e.g. Sand Submerged->Coastal Beach) or spectral similarities (e.g. Rock Submerged->Eelgrass) rather than true change, some are very likely real (Eelgrass->Sand Submerged; Wrack->Coastal Beach).

Table 11. Top ten habitat class change categories at each site and acres changed, ranked from high to low.

HODGKINS	Ac.	MANCHESTER	Ac.	MINGO	Ac.
Rock Submerged->Eelgrass	2.0	Sand Submerged->Eelgrass	6.7	Eelgrass->Sand Submerged	1.8
Eelgrass->Sand Submerged	1.5	Eelgrass->Sand Submerged	5.1	Sand Submerged->Coastal Beach	1.5
Sand Submerged->Algae Submerged	1.3	Sand Submerged->Coastal Beach	2.5	Sand Submerged->Eelgrass	1.0
Rock Submerged->Sand Submerged	1.2	Eelgrass->Rock Submerged	0.6	Coastal Beach->Rocky Intertidal	0.8
Rocky Intertidal->Coastal Dune	1.2	Eelgrass->Wrack	0.6	Eelgrass->Rock Submerged	0.7
Sand Submerged->Coastal Beach	1.1	Sand Submerged->Wrack	0.5	Wrack->Coastal Beach	0.6
Algae Submerged->Sand Submerged	1.0	Eelgrass->Coastal Beach	0.5	Algae Submerged->Coastal Beach	0.5
Sand Submerged->Eelgrass	0.9	Eelgrass->Algae Submerged	0.4	Rocky Intertidal->Coastal Beach	0.4
Rocky Intertidal->Coastal Beach	0.7	Coastal Beach->Rocky Intertidal	0.3	Submerged Rock->Eelgrass	0.4
Coastal Beach->Coastal Dune	0.7	Sand Submerged->Algae Submerged	0.3	Sand Submerged->Wrack	0.4

Of the possible total habitat area at each site, 60.6% changed at Hodgkins, 37.7% changed at Manchester, and 38.9% changed at Mingo Beach. When applied to a complex mix of habitats at the meso-scale, this change analysis method was difficult to interpret in light of classification errors, minor image collection inconsistencies and image quality issues; and this methodology would be more useful when applied to a smaller study area for fewer habitat classes.

4.4 Other opportunistic imagery uses

This study opportunistically found there is great potential to use drones to collect imagery to track impacts to coastal habitats. Specific to eelgrass, at all study sites the scars caused by boat moorings were highly visible and able to be classified as submerged sand surrounded by eelgrass (Fig 13). As such, these scar areas could potentially be quantified and tracked over time. Using a lower flight elevation along with additional passes would facilitate more accurate measurement of scar areas. Similarly, the same technology could be used to track subtidal impacts from dredging, intertidal impacts from shoreline construction activities, and beach changes due to storms, nourishment or hardening projects.

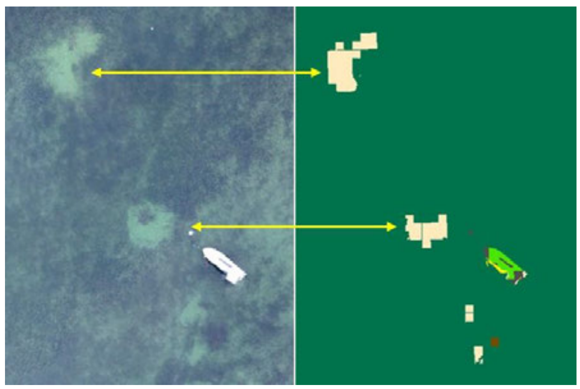

Figure 13. Demonstration of boat mooring scar detection in drone imagery and classification results (Manchester, 06/07/20)

Chapter 5. Discussion and Recommendations

This project was a proof of concept for using drone-derived imagery to map and track temporal change among complex coastal habitats. It resulted in a first-of-its-kind standardized workflow for drone imagery processing and machine classification in ArcGIS Pro.

In Massachusetts, there is a need to accurately inventory coastal habitats and monitor change in light of increasing coastal stressors such as development, water quality impairment and climate change. Existing statewide mapping programs do not take place at high enough spatial or temporal resolution to measure acute changes that can occur in habitats like dunes, beaches, salt marshes, eelgrass meadows, rocky intertidal areas, or sandy seafloors. Other habitats like beach wrack are not currently mapped by any programs in the state. Drones are an easily deployable meso-scale mapping tool that can supplement existing small- and large-scale programs with very high resolution imagery. Analysis of the imagery can elucidate the nature of habitat loss and a quick turn-around of data can allow for a more timely management response. In addition, drones may be able to address the need for high resolution habitat mapping for certain types of environmental permitting, enforcement actions, restoration efforts, and resiliency planning.

With proper planning, image capture can run smoothly and efficiently in the coastal environment, even given the unique challenges that a sandy and wet environment can present. Adhering to the optimal flight conditions is paramount, especially in temperate Massachusetts waters where every bit of light is needed to see through the water column, but any bit of glare can cause classification issues. Other considerations like site access, private property, and groundtruthing logistics must be weighed in project planning. For mapping over water, installation of ground control points can increase mosaicking success but create logistical challenges. This study found mosaicking to be possible (e.g. to at least a portion of the deep eelgrass edge) without GCPs, however incorporating them would result in more consistent and predictable orthomosaic coverage over subtidal habitats. Sites with a cove-shaped shoreline, nearby offshore features (e.g. emergent rocks), or shallow high-contrast habitats may not require many GCPs as mosaicking software can detect such features and use them in tie-point generation.

At the outset of this project, the hope was that segmentation and classification could be used on drone imagery to produce large polygons encompassing each habitat type, with a fine level of detail along the habitat edge, and an appropriate minimum mapping unit (MMU) that would group patchy areas together. For example, the preference was to group all rocky intertidal areas into one or few segments that comprised all the spectral variability within that class, rather than thousands of smaller segments within that class (Fig 8, lower inset). Similarly, the hope was that patchy eelgrass areas would be grouped together and mapped as a continuation of the larger meadow. However, the use of extremely high resolution imagery coupled with low spectral and spatial segmentation settings was problematic over water, and higher detail along with a maximum segment size were necessary to produce classifiable rasters. It is possible that better segmentation results could be achieved using a similar workflow in another software (e.g. Pix4D, Agisoft Photoscan); or by processing upland and subtidal areas separately using different settings.

While the segmentation process did not go as smoothly as anticipated, the use of the Support Vector Machine classifier created very finely detailed habitat maps that were especially accurate for eelgrass and rocky intertidal habitats. SVM was moderately accurate for coastal beach, submerged rock and submerged sand habitats, but performed quite poorly for salt marsh, dunes and wrack. Poor classification accuracy may have been caused by small sample size, errors in groundtruthing or reference datasets, or spectral similarities among classes. At Hodgkins Cove, for example, the algae growing atop rocky intertidal areas, vegetation in the dunes, and drifting submerged algae were frequently misclassified as salt marsh (Fig 9). Adequate groundtruthing could not be performed in these areas due to private property, which may have accounted for some of the classification error (15.4% accuracy in summer and 18.2% in winter). Conversely, salt marsh habitat at the Manchester site was fully accessible and had greater classification accuracy (37.5% in summer and 50.0% in winter). In terms of sample size, the salt marshes present at the study sites were small fringing marshes. In the creation of accuracy assessment points, the tool used a stratified sampling design to assign a proportional amount of assessment points to each habitat, resulting in only 13 salt marsh points in Hodgkins Cove and eight in Manchester. It is possible that salt marsh classification accuracy would have been improved had the study sites contained larger and more continuous habitat with a greater number of training and accuracy assessment points.

There are advantages and disadvantages to a very finely-detailed segmented SVM classification process in terms of project purpose and scale. If the goal of a mapping program is high precision in acreage and distribution (e.g. patchiness) data for a habitat class, compared to lower-resolution aerial methods, this methodology is appropriate and quite accurate for many habitats if ample groundtruthing can be conducted. While the classification process is time consuming – especially when creating training and accuracy assessment points - efficiencies would likely be discovered over time with repetition, where perhaps accuracy is not assessed for every survey if methods have not changed; or training sites are seeded from the most recent survey instead of created new.

Although drones are not an effective rapid survey method over large geographic areas (e.g. entire coastline) due to flight and hardware limitations, there is great utility in incorporating drones into existing aerial survey programs to spot check and provide greater detail to discrete survey areas as needed. Further, drones and machine classification techniques are well suited for precise documentation and quantification of habitat impacts or improvements. For example, machine classification would allow for the calculation of habitat loss from the construction of a boat ramp that extends across dunes, rocky intertidal and eelgrass areas, and mitigation requirements could be determined for each habitat type. Similarly, restoration projects could greatly benefit from this form of mapping. Detailed maps showing vegetation patchiness and continuity can inform the evaluation of success at salt marsh, eelgrass and dune restoration sites. Boat mooring scars, for example, could be tracked over time after converting the chain mooring to an environmentally-friendly design – a restoration strategy growing in popularity. Furthermore, as more of the Massachusetts coastline becomes hardened with riprap, seawalls, and breakwaters in light of sea level rise, the response of nearshore habitats at newly armored sites could be better understood using this methodology.

In order to integrate this methodology into a mapping program, some known issues around classification accuracy need to be resolved. While eelgrass and rocky intertidal areas were consistently mapped with mean overall accuracies > 80%, several habitat types were fraught with errors. Possible reasons include sub-optimal image collection (Tables 1 & 3), small extent (i.e. sample size) of some habitats relative to others, errors in reference data, and classification errors. Classification errors can be caused by water surface interference, spectral similarities among classes, lack of training data, and training data errors. Training data were particularly challenging for this project and were a significant shortcoming of this methodology. With access to some upland habitats impeded by private property and access to subtidal areas impeded by lack of boat, older data from other remote survey methods were used. With differences in the timing, scale and resolution of those data sources there are inherent errors in using them for classifier training. To improve accuracy, more thorough groundtruthing would be needed. Image processing and classification results would also have been improved by use of elevation data to improve marsh and dune detection, and use of infrared sensors to improve vegetation detection.

Heads-Up boundary digitization may still be the most time efficient method of mapping if habitat extent at a coarser scale is acceptable. While much faster to achieve, results from Heads-Up will lack the high resolution detail afforded by object based classification, thus risking the over-estimation of habitats that tend to have a more patchy nature (e.g. thin choppy wrack lines on the beach, areas of patchy eelgrass). Therefore, a hybrid approach may be appropriate, where Heads-Up is used for more rapid, coarse habitat assessments and SVM classification used to gain precision, visualize patchiness and refine habitat acreage estimates. For example, the mackerel pattern that eelgrass exhibits in Manchester was easily detected and accounted for in machine classification but lost in Heads-Up delineations (Fig 11), accounting for a nearly 12 acre difference. If resource managers were interested it tracking changes to the overall extent of this meadow, the Heads-Up approach would suffice. However, if precise eelgrass distribution needed to be tracked to assess impacts caused by boat anchoring impacts (a real example, in this location), more detailed habitat patchiness and acreage information would be warranted since impacts within the meadow might not correspond to any changes in the overall meadow extent.

If Heads-Up delineation of drone imagery were to be used for resource management, it would be critical to standardize the scale and MMU at which the interpretation would be performed, as is the case in any remote sensing work. Difficult questions around manual interpretation include how small, large, near or far habitat patches (or bare patches within contiguous habitat) need to be for inclusion or exclusion from the polygon. Of course, ecologically, patches and low-density areas may be just as important as continuous habitat, so in a management context it may be important to keep them within the polygon. While reliance on drone imagery is not feasible at the state-wide scale of DEP's mapping programs, it would be an appropriate tool for spot-checking or providing greater detail at areas of interest.

The three change detection approaches tested were each helpful in their own right. A Heads-Up approach offered a more rapid comparison of habitat extent and acreage over time when looking just at eelgrass and salt marsh. However if all habitat types were delineated, and numerous orthomosaics were processed in a time series, the time would add up quickly to the point where there may be a trade-off with machine approaches. Habitat area calculations based on classified pixel counts provided precise tabular data that was easily compared over time. While this method folded misclassification errors into the calculations, it is believed to be reliable for habitat classes with high accuracy. A downside is that it lacked a visualization component showing where change occurred. The Detect Change geoprocessing output was found to have great potential for detailed temporal monitoring that includes habitat class change-to and change-from information. The output was far too complicated to interpret at the meso-scale with up to nine habitat classes interacting with one another. However, this option would be especially useful when simplified via query for the desired habitats (e.g. showing only where salt marsh turned into beach over time). As with most decisions in habitat mapping, the best approach depends on the goals of the mapping effort.

This work demonstrated that a consumer-grade drone can collect very high spatial and temporal resolution imagery across the upland-to-subtidal coastal habitat gradient. Imagery can be classified to map a suite of complex and interactive habitat types, and when the process is repeated over time and in optimal flight conditions, drones can be a successful part of a meso-scale monitoring framework capable of detecting change.

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