UAV ANALYSIS OF RIVER HABITAT FOR ATLANTIC SALMON CONSERVATION

by

Chantal Giroux

Submitted in partial fulfilment of the requirements
for the degree of Master of Science

at

Dalhousie University
Halifax, Nova Scotia
November 2020

Dedicated to Roland Giroux for always believing in me.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Species distribution models (SDM) use presence data and environmental layers to predict spatial distribution of species. SDM could be used to denote important habitat for river restoration of endangered species such as Atlantic salmon. However, the extraction of environmental layers from rivers is complicated due to flow, light penetration, turbidity and refraction. This thesis presents two studies that look at the accuracy and feasibility of using unmanned aerial vehicles (UAV) to extract environmental data from the Upper Salmon River. The first study demonstrates the high accuracy of substrate size analysis from a UAV created orthomosaic. The second study creates slope and flow layers from a digital elevation model (DEM) created from UAV imagery, as well as substrate and presence data to model an accurate SDM of important spawning habitat. This shows the potential of UAVs and the further need to explore the use of SDMs in river habitat.

LIST OF ABBREVIATIONS USED

SDM	Species Distribution Model
LiDAR	Light Detection and Ranging
UAV	Unmanned Aerial Vehicle
DEM	Digital Elevation Model
IBoF	Inner Bay of Fundy
SFM	Structure From Motion
DFO	Department of Fisheries and Oceans
GPS	Global Positioning System
OBIA	Object-Based Image Analysis
RGB	Red Green Blue
COSEWIC	Committee on the Status of Endangered Wildlife in Canada
ASCII	American Standard Code for Information Interchange
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
AGV	Above Ground Vegetation

ACKNOWLEDGEMENTS

First, I would like to thank my supervisor Jon Grant, as well as my advisory committee, Ramon Filgueira, Paul Hill and Craig Brown for their advice and help in guiding me through this process. Thank you to Michael Stokesbury for agreeing to be my external examiner. Thank you as well to Kurt Samways and his crew, for without his expertise and data, this thesis would not have been possible. Additionally, thank you to Craig Brown for joining my committee with very short notice, and his invaluable insight into ArcGIS.

Secondly, I would like to thank Corey Clarke, Bruce Persaud and all the folks at Fundy National Park, who helped me in the field as well as allowed us to use their facilities. This work would not have been possible without their assistance.

Thank you to Jeffrey Barrell for all his help and companionship, through field work and navigating academic life. Without Jeff, the field work would not have been complete, or at least not with nearly as much fun.

I would also like to thank Christopher Greene, Jennifer Strang and all the folks at the GIS center at Dalhousie University who helped me develop and perfect the methods I used. As well as the Department of Oceanography, in particular Lori Lawton, who was often my go to whenever I had questions.

Thank you to the Grant lab, both old and new, for the support and companionship through this process. Special thanks to Anne McKee, Marianne Parent and Stephen Finnis for often being my sounding board when I was having issues.

Lastly, a special thank you to my family, Diane, Jean-Luc, Jean-Francois, Jean- Pascal and Mireille Giroux for being incredibly supportive during this process, and for always believing I could accomplish it. Bob and Biscuit, for keeping me sane during this process and Matt MacLean, for helping keep me alive, while I delved into my work and forgot to eat and sleep. This would not have been possible without all of you.

CHAPTER 1 INTRODUCTION

Rivers are critical habitat for many species, their complexity through elevation, substrate and flow allowing for niche habitats (Gorman & Karr, 1978; Schumm, 2007). The use of habitat can differ based on life stage (Kocik & Ferreri, 2011), or seasonally (Heggenes & Saltveit, 1990). Certain species, such as diadromous fish, require this diversity to help facilitate the survival of juvenile fish by altering their behavior and growth (Finstad et al, 2007; Clarke et al, 2016). An increase in microhabitats allows for an increase in species diversity, density, and predator avoidance (Schlosser, 1987; Holbrook & Schmitt, 2002; Casatti, 2005; Lapointe, Corkum & Mandrak, 2007). Changes in river environment that reduce their physical complexity can lead to negative effects on populations (Horan et al., 2000; Venter et al, 2008). The potential for river restoration to prior state relies on the understanding of the physical composition, three-dimensional complexity and the use of these components. Species distribution models (SDM) can be used as a method to understand these variables, and how environmental characteristics affect habitat use and spatial distribution. SDM relies on environmental data and presence/absence data to predict species distribution (Elith & Leathwick, 2009). This is accomplished by observing the environmental patterns at the presence locals to understand how they affect spatial distribution. Used in a variety of fields, SDMs are particularly important in conservation as a spatial planning tool (Johnson & Gillingham, 2005). Understanding the geographical extent of a species is crucial to its management and conservation and can allow for forecasting (Lawler et al., 2011). Although commonly used for terrestrial environments, SDM are more challenging to implement in aquatic environments where environmental data is harder to acquire due to flow, light penetration, turbidity, and refraction (Woodget et al., 2015). To understand how habitat characteristics can affect abundance and begin mapping SDMs, adequate environmental data must first be gathered. Current methods of extracting environmental data from rivers include LiDAR (light detection and ranging), which is costly, or in situ surveys, which are not only time consuming, but hard to implement on a broad scale. More recently, the use of unmanned aerial vehicles (UAV) or drones have begun to be explored as a cost effective, rapidly deployable, and high-resolution alternative. Although preliminary, this research has already shown promise in the analysis of substrate within rivers using orthomosaics (Arif et al., 2017; Danhoff & Huckins, 2020), as well as the creation of digital elevation models (DEM) from UAV (Tamminga et al, 2015). With the varying physical conditions within the river, the accuracy of a substrate analysis using UAVs through changing flow, and depth of macrohabitats remains to be seen.

Pools, riffles and run exist as descriptive classification to delineate sections of differing flow, depth, and substrate. Pools are generally characterized by deeper, slower flowing water. Riffles on the other hand, are shallower with a faster flow and have breaks in the water surface. Runs have a moderate depth and flow, with no breaks in the water surface. As physical conditions within the classes are similar, this classification is often used to partition rivers for sampling (Jowett 1993). These classes have also been used to assess habitat use of fish (Rimmer & Paim, 1983). As this classification sections the river based on similar physical characteristics, it is ideal to test the accuracy or precision of a UAV substrate analysis. If UAVs are seen to be viable option for analysis, mapping could be used to help threatened species such as the Atlantic salmon, *Salmo salar*.

Atlantic salmon are found spread across the Atlantic from Canada to the Baltic

Seas, including rivers located in America, Spain, France, the UK, Ireland, Norway, Sweden, and Finland (Hendry & Cragg-Hine, 2003). Important for food, social and ceremonial purposes of first nation communities, the salmon are also valued for recreational activities and eco-tourism (Fisheries and Oceans Canada, 2018). Anadromous, they migrate up freshwater rivers to spawn in the late fall, incubating over winter before emerging in the spring as fry (Hansen & Quinn, 1998). They spend the first 2-4 years of their lives as parr in rivers before undergoing the smoltification process and entering the ocean (Mills, 1989). The post-smolt mature in the ocean, generally after one winter, before returning to their native rivers to spawn (Thorstad et al, 2011). Unlike their Pacific counterparts Atlantic salmon can have multiple spawning seasons (Jonsson, 1991). Connecting both the freshwater and saltwater systems through their migration, they are also important indicators of environmental quality (Fisheries and Oceans Canada, 2018). In recent years, they have seen a large decline in the abundance of returning salmon due to a variety of stressors, including pollution, dams, dewatering of streams, as well as other factors at sea (Parrish et al., 1998; Limburg & Waldman, 2009). There have been six regional groups of North American Atlantic salmon identified (Verspoor, 2005). Certain populations have been more affected than others, such as the Inner Bay of Fundy (IBoF) salmon. The IBoF salmon are found ranging between the Mispec river in New Brunswick to the Pereaux river in Nova Scotia. Designated as endangered by the Committee on the Status of Endangered Wildlife in Canada in 2001, IBoF salmon have seen population declines of up to 97% (Irvine et al., 2005).

IBoF salmon occupy 32 of the 48 rivers in the Inner Bay of Fundy, a large embayment estuary located on the coasts of Nova Scotia and New Brunswick (Gibson et al., 2003). Due to the declines in populations and the extended time they spend in the rivers, many projects have sought to do river restoration and salmon reintroduction (Einum et al., 2008; Trzcinski et al., 2004). The problems arise in determining which rivers will have the largest benefit in restoration, and where on the rivers should these efforts be concentrated. SDM could inform this analysis if suitable environmental layers were developed from the river.

This research seeks to determine the accuracy and feasibility of drones to identify salmon spawning grounds. This was conducted through two branches of investigation. As substrate is a vital component of spawning salmon (Fjellheim, et al., 2003), Chapter 2 looked at the accuracy of extracting substrate size from orthomosaics through the varying physical characteristics of pools, riffles and runs. Chapter 3 studied the creation of an SDM using environmental layers (slope & flow) extracted from a DEM, along with substrate from an orthomosaic and presence data to determine habitat preference of IBoF salmon within the Upper Salmon River.

CHAPTER 2 THE USE OF UAVS TO QUANTIFY SEDIMENT GRAIN SIZE THROUGH VARYING MACROHABITATS

2.1 INTRODUCTION

Rivers are complex habitats with often steep gradients in elevation, substrate type, flow, and depth (Schumm, 2007). In addition, they interface with the coastal ocean as a link between terrestrial and marine habitats. Fish and invertebrates exploit the variety of river habitats as do mammals and birds (Schneider & Winemiller, 2008; Rushton & Carter, 1994; Dubuc et al., 1990). Diadromous fishes such as salmonids require the full diversity of river and marine environments to complete their life cycle. Since rivers are so integral to terrestrial landscapes, they are often subject to human disturbance including dams, siltation, course alteration, eutrophication and other changes in water quality (Wohl, 2005; Hamilton, 2002; Hilton et al., 2006). These alterations interact with climate change in negative ways, e.g. deforestation reduces both shade availability, by removing riverside vegetation (Garman & Moring, 1991) and bank stability, by removing the roots that anchor the soil (Horton et al., 2017). Changes to river habitat quality affect multiple species that depend on river structure and function for their life histories that include feeding, growth, reproduction, and migration (Thorstad et al, 2008).

An understanding of the variety of river habitats, their arrangement in the riparian landscape, and relationship to useable habitat are critical in conserving river species. Habitat structure refers to the physical composition and three-dimensional complexity of an area (McCoy & Bell, 1991). In river environments, this complexity can refer to current velocity, structural density, rugosity, porosity of substrate and substrate diversity (Willis et al, 2005). Increased complexity creates microhabitats that increase the niche space and species density in aquatic environments (Schlosser, 1987; Holbrook & Schmitt, 2002). Moreover, the potential for river restoration requires this information to ensure that physical structures are reconstructed at the appropriate spatial scale and diversity to provide suitable habitats (Finstad et al., 2007).

Species distribution modelling (SDM) attempts to match presence/absence of a given species with habitat features to understand how habitat affects distribution (Elith & Leathwick, 2009). The essential component of SDM is the ability to spatially characterize habitat. Statistical models may be used to delineate the importance of upstream-downstream gradients in fish distribution (e.g. Buisson et al. 2008). Despite the importance of habitat categorization to describing river systems, there are relatively few examples that address detailed mapping of river habitat. For groups such as salmonids, habitat use is specific to egg deposition, juvenile feeding and predator avoidance. Habitat distribution for each life stage could be mapped based on the various physical requirements. Atlantic salmon (*Salmo salar*) spend between 2 to 4 years of their life in rivers as parr (Mills, 1989), with subsequent smoltification and either single or multiple migrations between river and sea.

Habitat mapping is used to show the geographic distribution of an organism. Because many river areas are isolated and/or inaccessible, habitat mapping is particularly difficult. As with any aquatic habitat, water cover precludes visual access. Despite these issues, remote sensing has been used successfully in rivers, and the application of unmanned aerial vehicles (UAV) to river mapping is a growing research tool (Zinke & Flener, 2013; Rusnák et al., 2018). Structural complexity is a large influence on the success of Atlantic salmon in both hatcheries and in the wild. Therefore, understanding which rivers have areas of suitable substrate diversity is vital for the recovery of the species. The current methods used in river habitat surveys include LiDAR (light detection and ranging), which is costly (Woodget et al, 2015), or in situ surveys, which are time consuming and difficult for broad scale analyses. Beyond LiDAR, there have been rapid advancements in technology, UAVs or drones have become easy to use, rapidly deployable, high resolution and inexpensive research tools for remote sensing (Saska et al, 2012.; Tang & Shao, 2015). High resolution aerial images coupled with GPS and altitude data are used to model river morphology in a 3D approach referred to structure from motion (SFM) (Westoby et al., 2012). This approach matches features in overlapping images to create a three-dimensional model using photogrammetry, in addition to producing an accurate orthomosaic of the area. Using SFM on drone imagery DEMs (digital elevation models) and orthomosaics can be created, from which detailed information can be extracted about the substrate and structural complexity of the terrain. Although these techniques are widely used in terrestrial ecology (Cunliffe et al, 2016) they are a newer tool for analysis of riverbed morphology (Lane, 2000). Photogrammetry used in river habitat can run into issues regarding the depth of light penetration, turbidity, reflection and refraction in submerged areas (Woodget et al, 2015), but this technique is still applicable to model river topography and substrate analysis for fluvial morphology studies (Lane, 2000; Woodget et al, 2015; Arif et al, 2017).

In the North Atlantic, Atlantic salmon are an iconic anadromous species, threatened or endangered throughout much of their range by river destruction, overfishing in freshwater and at sea, climate warming, as well as predation and changes in pelagic food webs (Amiro, 2009). Rivers are the location of spawning and growth of early life stages, and juvenile fish spend several years in freshwater with subsequent returns (Jonsson et al., 1991). Many eastern Canadian populations undergo long distance ocean journeys to Greenland, with reduced survival at sea (Dadswell et al., 2010). However, other populations in the Bay of Fundy and Gulf of Maine are restricted in migration, particularly those of the Inner Bay of Fundy (IBoF salmon) (Department of Fisheries and Oceans Canada, 2010). Most of these populations are critically endangered or their wild populations extinct in individual rivers, only remaining in existence in part by captive breeding and re-stocking programs.

IBoF Atlantic Salmon have recently seen population declines of up to 97% (Irvine et al, 2005). With these rapid decreases in population, there has been an increase in projects seeking to restore breeding habitat (Einum et al, 2008), including a recovery strategy from the Government of Canada (Trzcinski, et al, 2004) and reintroduction through captive rearing programs (Clarke et al, 2016). Compromises to many of the ~40 rivers used in their life cycle play an important yet unknown role in their early life history. Protected areas such as those in national parks (e.g. Upper Salmon River in Fundy National Park) serve as templates for healthy river ecosystems and the distribution of natural habitats within these environments.

Fundy National Park is the site of a major salmon recovery project formed as a partnership between Parks Canada, Cooke Aquaculture, Fort Folly First Nation, University of New Brunswick, and Dalhousie University (Clarke et al, 2016). Running through Fundy National Park is the Upper Salmon River (USR), which is thought to be devoid of native salmon populations due to logging dams placed in the early 1900s (Dadswell, 1968). The dams have since been removed and salmon restoration efforts are underway. Using the live gene bank established by the Department of Fisheries and Oceans (DFO), genetically diverse wild salmon were reared from wild smolts (Clarke et al, 2016). These juveniles were then released into the rivers, before subsequently being recaptured and reared to maturity in marine net pens to increase adult survival rates. The adult salmon were then rereleased into the river for breeding. The rearing strategies employed in the Upper Salmon River led to the discovery that releasing juveniles before the onset of feeding increased their mass and fecundity over those that were kept in captivity for longer (Clarke et al, 2016), highlighting the importance of habitat in early life history. If this program is to expand to other rivers in the Inner Bay of Fundy, an assessment of available habitat is required to determine which rivers are best suited for restocking and/or restoration.

The goal of this research is to delineate salmon habitat based on substrate type in a pristine river via use of an UAV. Specifically, I explore the capability of a drone to determine substrate grain size as a component of structural complexity for salmon spawning habitat with the following objectives:

- Test the utility of UAVs to obtain high resolution aerial imagery of a protected river used for salmon restocking and analyze the imagery for substrate size.
- Evaluate the accuracy and validate the image-based substrate classification through varying macrohabitats to see the effects of physical characteristics (flow and depth) on imagery.
- Compare substrate settlement in macrohabitats with known salmon preference

to evaluate if macrohabitats can be used as an indicator of salmon spawning grounds.

2.2 MATERIALS AND METHODS

2.2.1 Study Site

The Upper Salmon River (45.599°N, 64.948°W) is located in Fundy National Park near Alma, New Brunswick, draining into Chignecto Bay in the Bay of Fundy (Fig. 1). An estuary with salt marsh and a macrotidal delta near the mouth of the river, it is considered critical salmon habitat by the Department of Fisheries and Oceans Canada (2010). The river, which descends from a plateau, was studied from the Forks, a junction with steep waterfalls that are considered the upper limit of salmon distribution, to near sea level. The study site includes 7 transects within ~10 kilometers that encompass the extent of the salmon habitat within the river (Fig. 1).

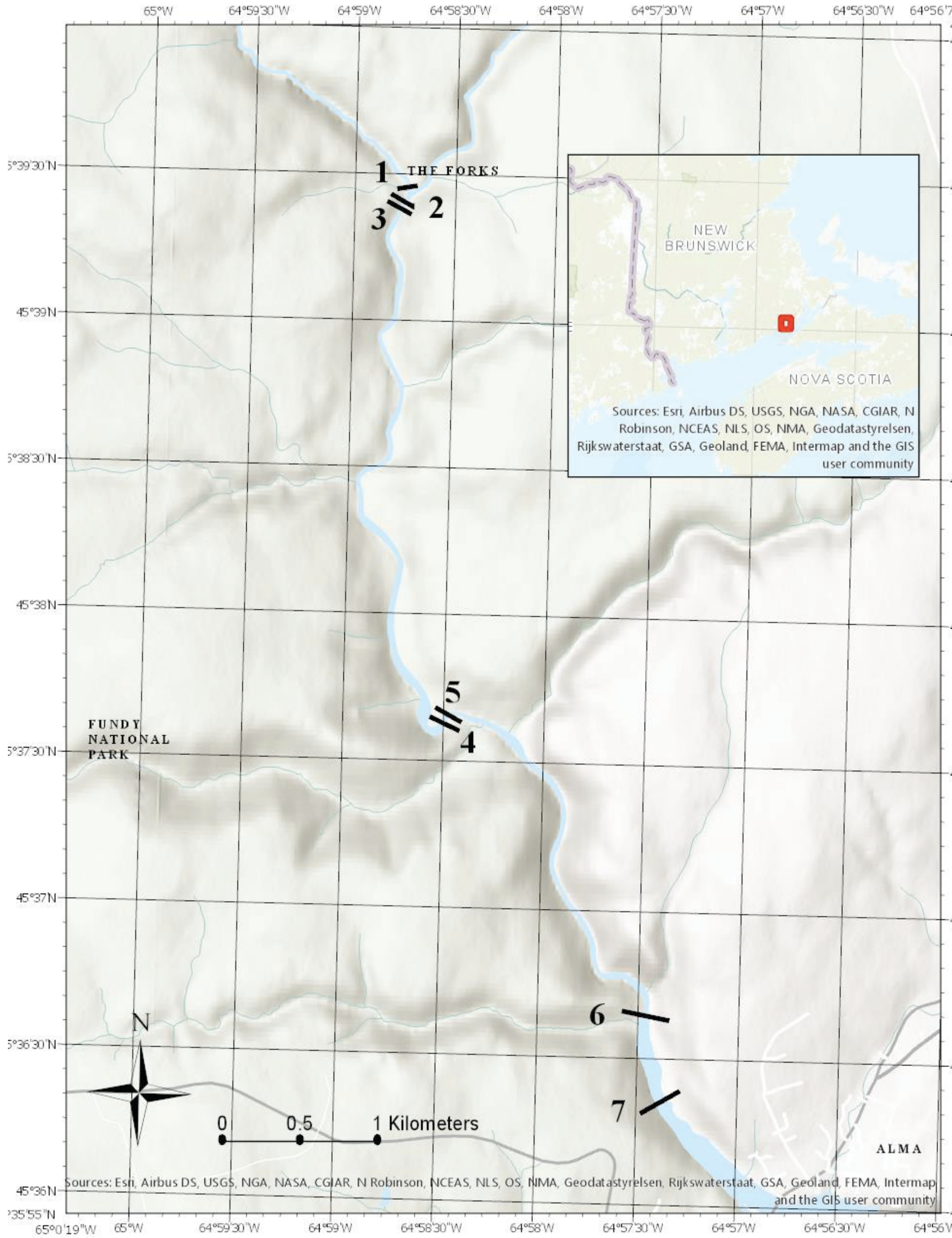

Figure 1: Map of the Upper Salmon River within New Brunswick. The black lines represent the 7 transects. The inset shows the location of the Upper Salmon River (red box) within New Brunswick.

2.2.2 Data Collection

2.2.2.1 Drone Data

Aerial imagery was collected using a DJI Phantom 4 drone at each of the transects described above, during times of low water level in the river, in late August. Drone positioning was calculated using the on-board GPS/GLONASS (global navigation satellite system), as well as the barometric pressure sensor for elevation. Imagery was taken using the high dynamic range, high definition camera standard on the DJI Phantom 4 drone. The drone was flown over the transects at 30 meters in height and encompassed >80% overlap in imagery covering the transect locations, above the 70% required by Pix4D. Still images were taken at 7 second intervals, with the drone paused in hover every 7 seconds to allow for clear imagery. This process was repeated for each transect location and included 730 images. The imagery was processed in the software package Pix4D, to create orthomosaics of each transect with a resolution of 1.7 cm per pixel.

2.2.2.2 Groundtruth Data

Groundtruth data were obtained by field inspection of the substrate at designated GPS (Global Positioning System) waypoints on transects, which were four quadrats wide and the length was the full width of the river, with each quadrat measuring 1 m^2. Transects were placed in each of the river geomorphological zones, referred to herein as macrohabitat: (1) pool/riffle, (2) pool, (3) run/riffle, (4) pool/run, (5) riffle, (7) run. An additional run transect was added at the long-term monitoring site (6) as it is a well-studied area of the river. Pools are generally characterized by a slow current with deeper water. Riffles are shallow areas with fast turbulent water, often with rocks protruding through the surface. Runs have a moderate current and depth, with a continuous water surface, and connect areas between riffles and pools. Although parameters exist to denote depths and water velocities of these macrohabitats, the classification is often subjective and analyzed visually (Jowett, 1993; Vadas & Orth, 1998; Ward, 2003). The pool, riffle, run classification is often used by biologists to identify spawning habitat (Gibson, 1993). As salmon spawning habitat is characterized by shallow, faster water, it generally correlates with areas categorized by riffles, runs or the tail ends of shallow pools. Since these different zones contain different depths, and flow, both of which affect clarity, this classification method was chosen to select transect locations, and to test the ability of the drone to capture imagery in the differing physical conditions found in river macrohabitats. Zones were identified visually by water flow and depth.

The substrate was classified within the quadrats, within each transect based on sediment grain size (Table 1), ranging from silt to bedrock (Borsányi., 2004). However, GPS mapping inconsistencies in the field team led to transects being unusable, with only transect 1 being properly situated. Therefore, the data from transect 1 was used to validate the results rather than inform them. For designation of wet, dry and riverside vegetation (RV) segmentation (see below) on the drone collected transects as well as substrate classification through object-based image analysis (boulders, gravel etc.), visual inspection of the orthomosaics was adopted. Although the GPS locations of substrate classes at each transect could not be verified, the designation of classes observed on the ground was still used qualitatively to validate comparison to classes visually designated in aerial images.

Table 1: Size classes used to classify substrate for the groundtruth data.

Class	Substrate
1	Silt
2	Sand (0.063-2mm)
3	Fine gravel (2mm-2cm)
4	Gravel (2-5cm)
5	Large gravel (5-20cm)
6	Boulders (20-40cm)
7	Large boulders (>40cm)
8	Bedrock
9	Vegetation

2.2.3 Classification

The substrate classification was based on a similar study conducted by Arif et al. (2017). Transects underwent a simple supervised classification to separate RV, dry/exposed substrate and wet/submerged substrate (Fig. 2). This subsequently allowed for an accurate classification to be conducted through an object-based image analysis (OBIA) in PCI Geomatics.

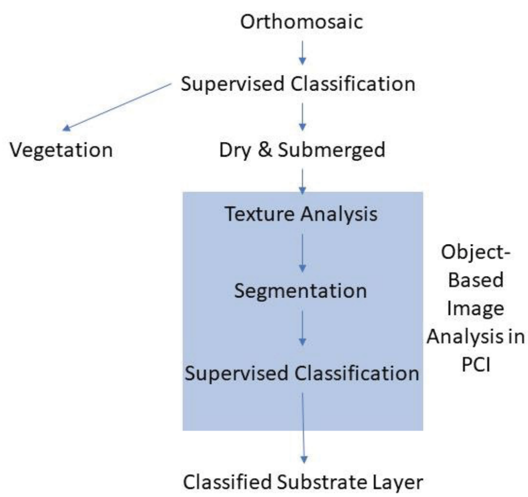

Figure 2: Data processing steps. The orthomosaic undergoes a supervised classification (ArcGIS) to separate the RV from the substrate. The substrate is then analyzed for texture. The pixel values of the substrate are used to segment the image into substrate sizes, which are assigned through another supervised classification in PCI.

2.2.3.1 Supervised Classification for Removal of Riverside Vegetation

Using ArcGIS, each orthomosaic was clipped around the transect locations to remove the edges and areas with insufficient overlap to be considered reliable (Fig. 3). Both wet and dry substrate categories were analyzed as habitat, since drone imagery was obtained during low water level where exposed substrate would equate to potential spawning habitat during the spawning season when the water is higher. A supervised classification involves user derived training sites for all the classes provided, using pixel information within the training site to segment and classify a given area. When selecting training sites, submerged substrate was considered to be any substrate that was underwater or wet. On each transect, sections were assigned using polygons, representing each of the classes, wet, dry and RV, for training. These training classes covered ~28% of the total area of all 7 transects. An object-based classification was used for sectioning into wet/dry/RV, which involved consideration of neighbouring pixels for their spectral (color) and spatial (shape) characteristics. These characteristics are part of the Image Classification Tool in ArcGIS pro and work on a scale ranging from 1-20 to determine how to section the image. A higher spectral value allows for a more detailed classification among objects, while a higher spatial value allocates a greater importance to spatial proximity of features, allowing for more clustered features. The ideal values for spectral and spatial detail to provide the best overall accuracy for all 7 transects were determined to be 17.90 and 15 respectively, based on visual assessment and the accuracy assessment. The image underwent the supervised classification after training sites were selected from the manually sectioned polygons (Fig. 3), the resulting images were 3 separate RGB (Red Green Blue) images of dry, submerged and vegetated for each transect. Vegetated areas were clipped with only submerged and vegetated areas being analyzed further.

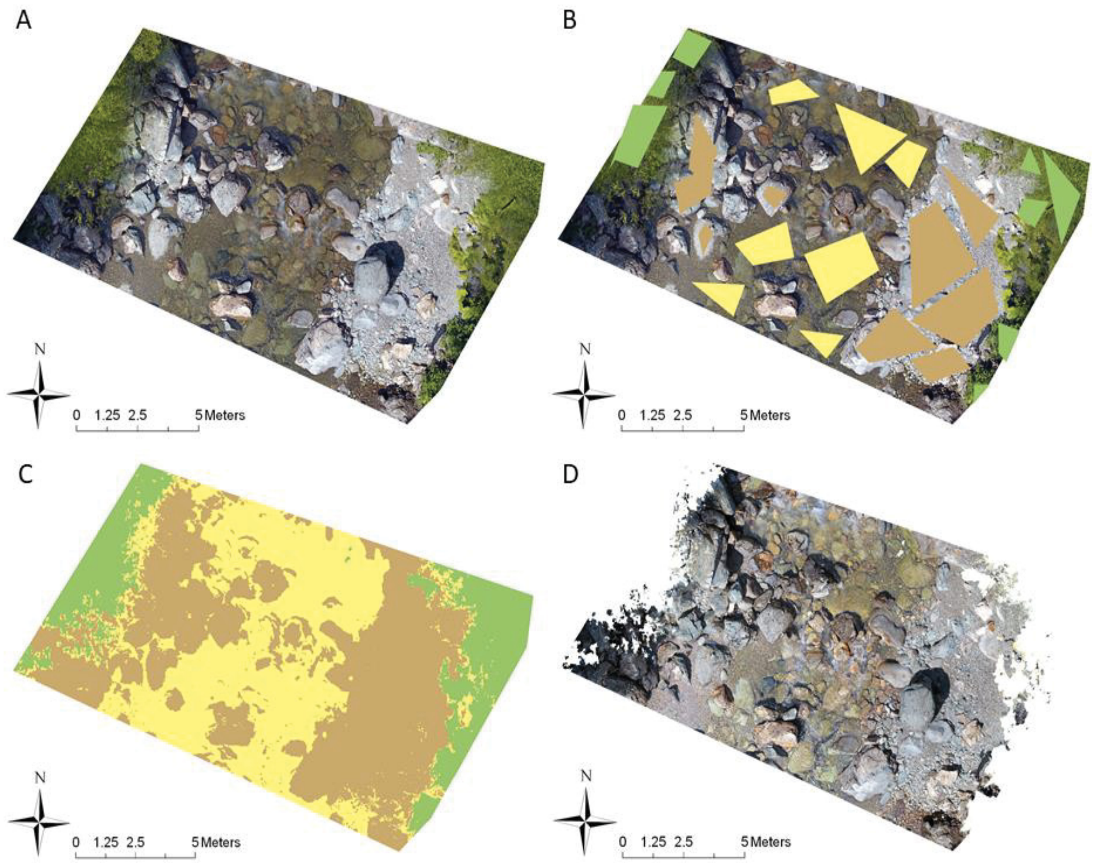

Figure 3: The process of classifying substrate demonstrated for transect 3. A. The transect segment from drone imagery. B. Training sites are selected with RV (green), dry (brown) and submerged (yellow). C. This produces classified shape files which are used to extract dry (brown) and submerged substrate (yellow) from the RV (green). D. The resulting RV free raster layer.

In order to assess the accuracy of the trained classification, 500 random points were selected by the toolset within the training polygons and omitted from training. Their predicted value (wet/dry/vegetated) was compared to the polygon designation. An error analysis was conducted by determining the % agreement between training categories and predictions from image analysis.

2.2.3.2 Substrate Classification Using Object-Based Image Analysis

An object-based image analysis (OBIA) first segments an image based on spectral similarity while considering neighbouring pixel values (Hossain & Chen, 2019). A portion of the segments are then assigned to training sites before undergoing a supervised/unsupervised classification to classify the remaining segments based on the attributes found in the training sites. For the OBIA of substrate type (Fig.4), the software package PCI Geomatics was used to create small segments within wet or dry sections based on the texture of the red band (homogeneity, contrast and mean intensity), evaluated on a 10 x 10 pixel grid (1.74 cm per pixel) (Fig. 5). Texture refers to the variations in intensity values of pixels (bumpy, rough, smooth, silky) and considers spatial relationships among neighbouring pixels by examining how often specific values of pixel pairs occur (Arif et al., 2017). Based on Arif et al. (2017) study, the submerged and dry images were run through the OBIA separately to increase accuracy. Substrate type based on visual designation was then assigned to a set of training segments (Fig. 4). As the PCI software relies on the manual designation of training and accuracy sites, fine gravel (0.2-2cm) was combined with the gravel (2-5cm) into a fine gravel classification referring to 2mm-5cm, as they were not visually distinguishable from one another. This was considered to be acceptable as both classes were considered to be ideal spawning substrate. Accuracy of this trained classification was quantified by comparing a separate set of predicted substrate types to visual assessment of the same segment. An error analysis was then constructed for each substate class but reported as overall % agreement between training and predictions. The number of segments allocated to accuracy assessment was dependent on the number of segments available, the size of the segments and the size of the transect. In total there were 94, 95, 86, 76, 107, 80, and 89 accuracy assessment segments assignments to transects 1, 2, 3, 4, 5, 6, and 7 respectively, with twice the amount of training segments than accuracy segments.

Finally, substrate type categorized in the method above was compared to field data on substrate collected in groundtruthing studies of transect 1 as a further assessment of training accuracy. To conduct this accuracy assessment, a visual assessment was done on the orthomosaic for transect 1 (pool/riffle transition zone), where the GPS locations of the groundtruth data were mapped over the PCI analysis. The substrate type was determined for each GPS location. An error analysis was conducted between both sets of data, similarly to the supervised classification.

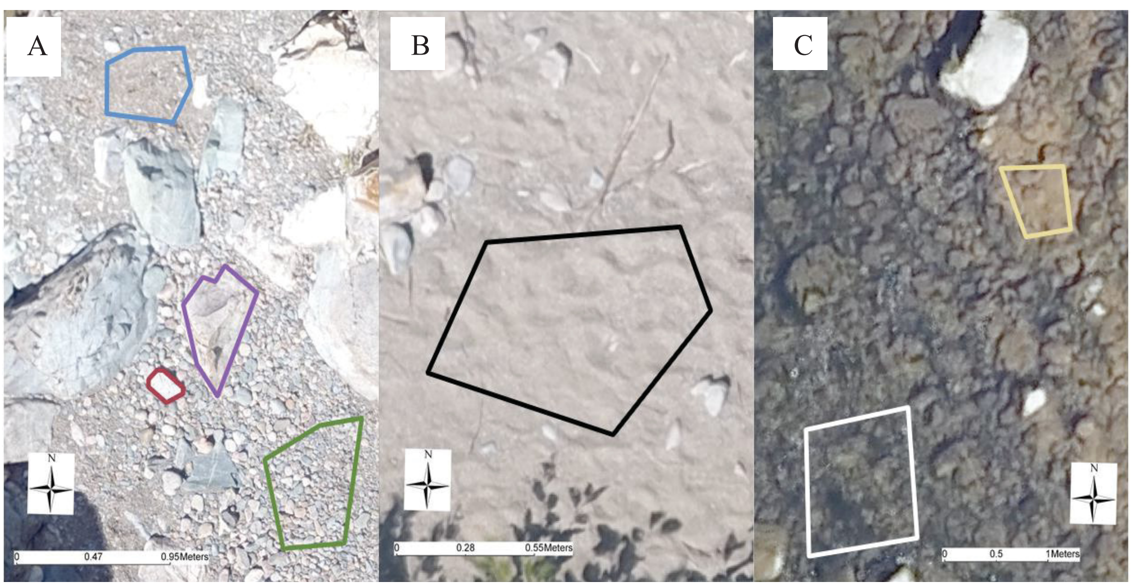

Figure 4: An example of ground cover samples used as training sites in the supervised classification of substrate in both dry and submerged environments. A. purple (large boulders), red (boulders), green (gravel), blue (fine gravel), B. black (sand), C. white (other vegetation), yellow (silt)

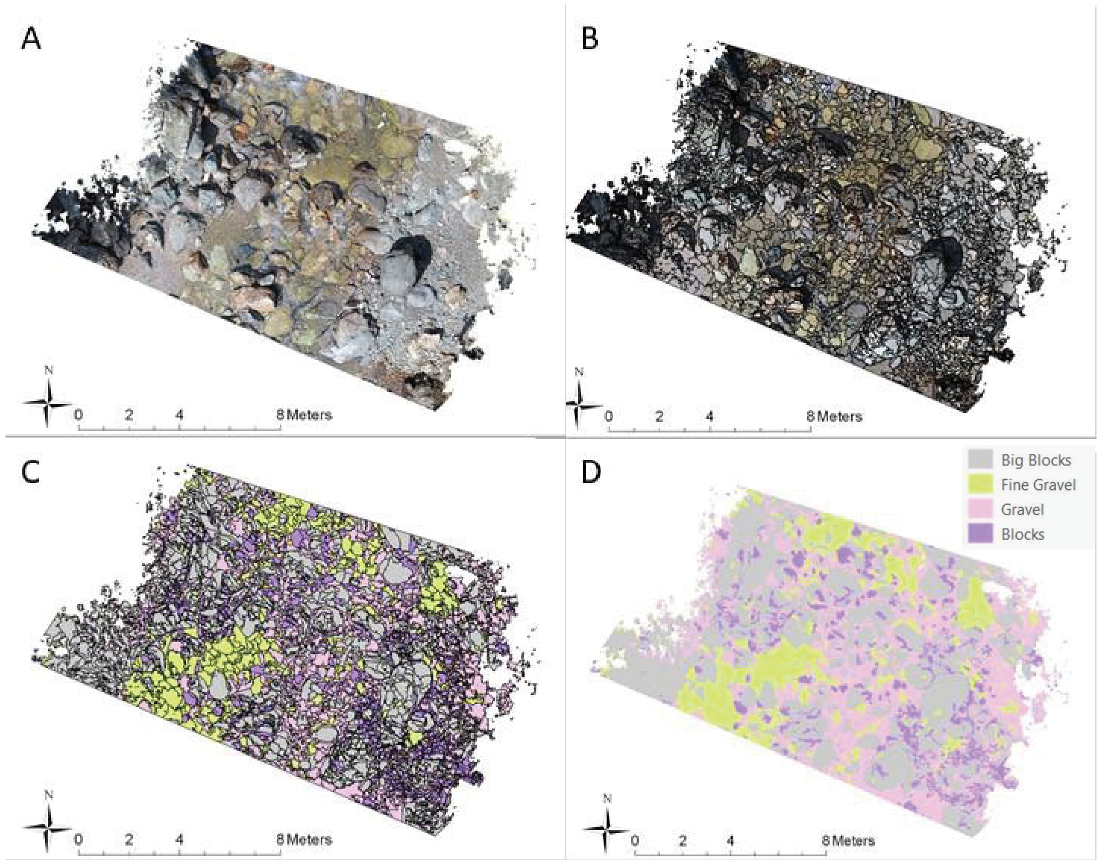

Figure 5: Example of the segmentation through object-based image analysis conducted in PCI Geomatics on transect 3. A. Dry/submerged classified image of transect 3. B. Segmentation overlayed on top of the dry/submerged image. C. Classified result of the segmentation. D. The results of the object-based image analysis on transect 3 with the segmentation outlines removed.

2.2.4 Spawning Habitat

Although measurements vary, Atlantic salmon have been reported to breed in substrate as small as 5.4 mm to as large as 100 mm (Armstrong et al, 2003), with 16-64 mm being considered an ideal range (Louhi et al, 2008). In the present study, fine gravel (2mm-5 cm) was considered to be ideal spawning substrate, recognizing that other factors (e.g. flow) are also considered in spawning habitat.

2.3 RESULTS

Imagery captured from the drone produced 7 orthomosaic images (Fig. 6), which were clipped and used to extract transect data. Transects 1-7 represented macroscale river habitat including pool/riffle (1), pool (2), run/riffle (3), pool/run (4), riffle (5), run/long term monitoring site (6) and the southernmost site (run; 7) respectively. Visual inspection indicated that the pool/riffle segment (Transect 1; Fig. 6.1) had large boulders with breaks in the surface of the water (riffles), followed by deeper, calm water with smaller substrate boulders (pool). The pool segment (Transect 2; Fig. 6.2) is dominated by deeper water and small substrate (fine gravel), interspersed with large boulders. The run/riffle segment (Transect 3; Fig. 6.3) had breaks in the surface of the water over large/medium substrate, followed by shallower calm water (run). The pool/run segment (Transect 4; Fig. 6.4) had shallow water dominated by medium substrate (run), followed by the deep, darker calm water (pools). The riffle segment (Transect 5; Fig. 6.5) had shallower water with breaks over the rocks. The run (Transect 6; Fig. 6.6) was dominated by medium substrate and consisted of shallower calm water. The long-term monitoring segment (Transect 7; Fig. 6.7) had shallow water dominated by small substrate and submerged vegetation.

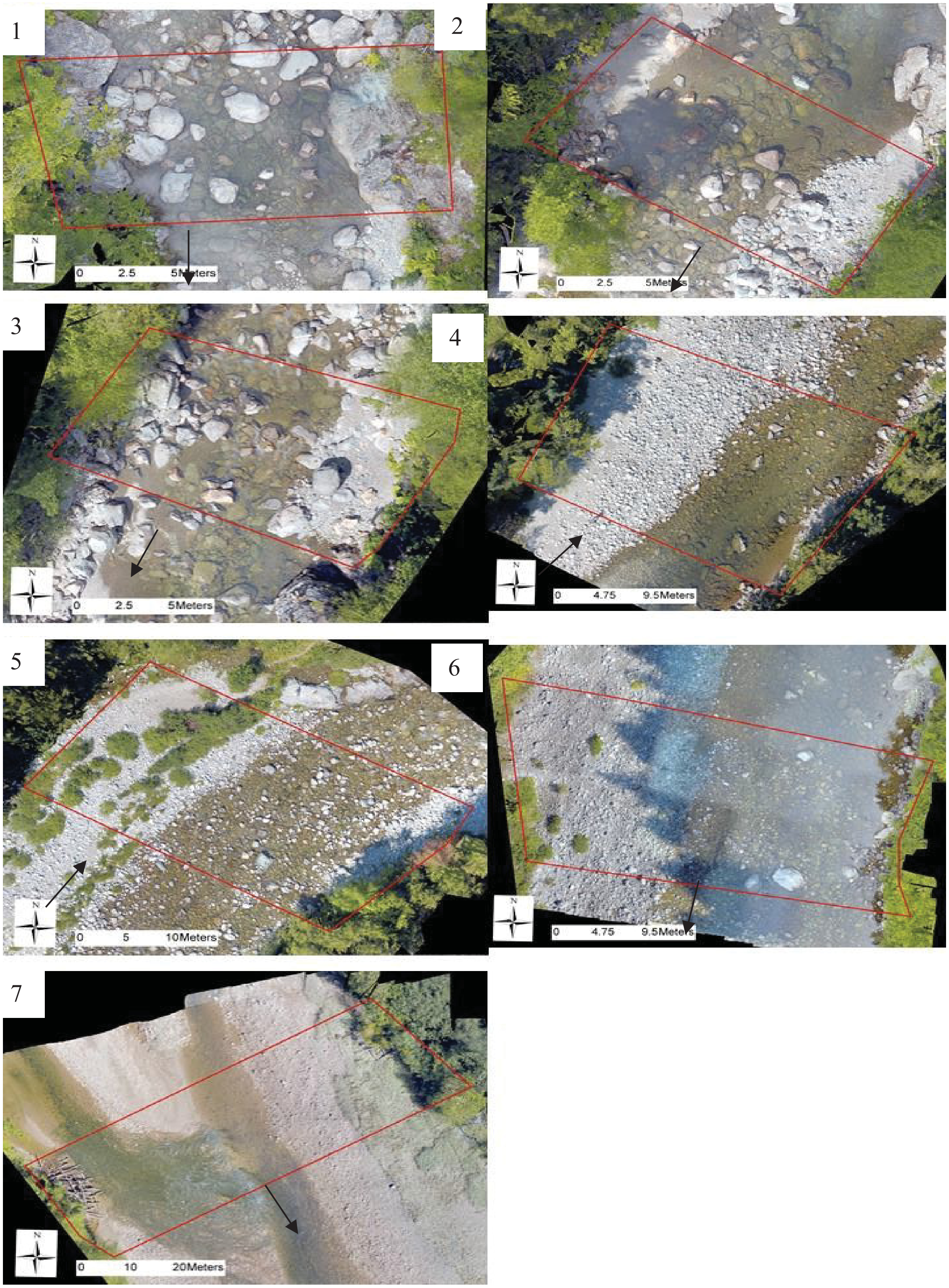

Figure 6: Orthomosaics for transects 1-7, transect areas denoted by the red boxes, with black arrows to indicate downstream flow direction. Transect 1: Pool/Riffle, Transect 2: Pool, Transect 3: Run/Riffle, Transect 4: Pool/Run, Transect 5: Riffle, Transect 6: Run/Long term monitoring site, Transect 7: Run (Lowermost Site)

2.3.1 Supervised Classification

The supervised classification was conducted over all 7 transects and extracted submerged substrate, dry substrate and RV (Fig. 7). Certain large boulders were classified as both submerged and dry substrate when they were observed to protrude out of the water. Using the training sites, substrate was extracted with minimal misidentification in the RV class, while submerged and dry substrate had some areas of misidentification. Areas of dry substrate shaded by RV were occasionally misclassified, but areas of dry substrate shaded by large boulders were not. Classification error is further quantified below.

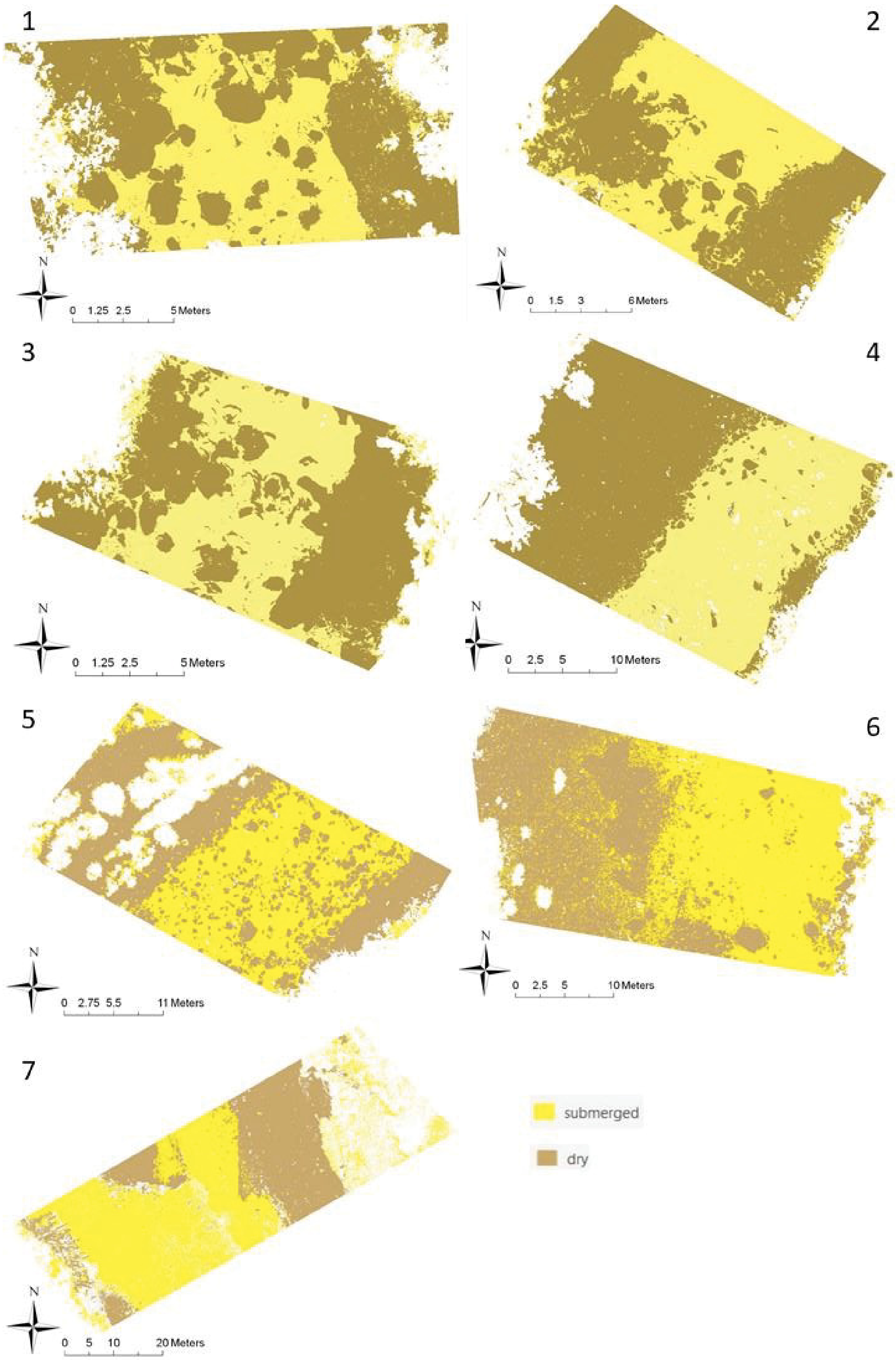

Figure 7: Classified orthomosaics for transects 1-7 with RV removed using a simple supervised classification. Yellow is submerged substrate and brown is dry substrate.

2.3.1.1 Accuracy Assessment

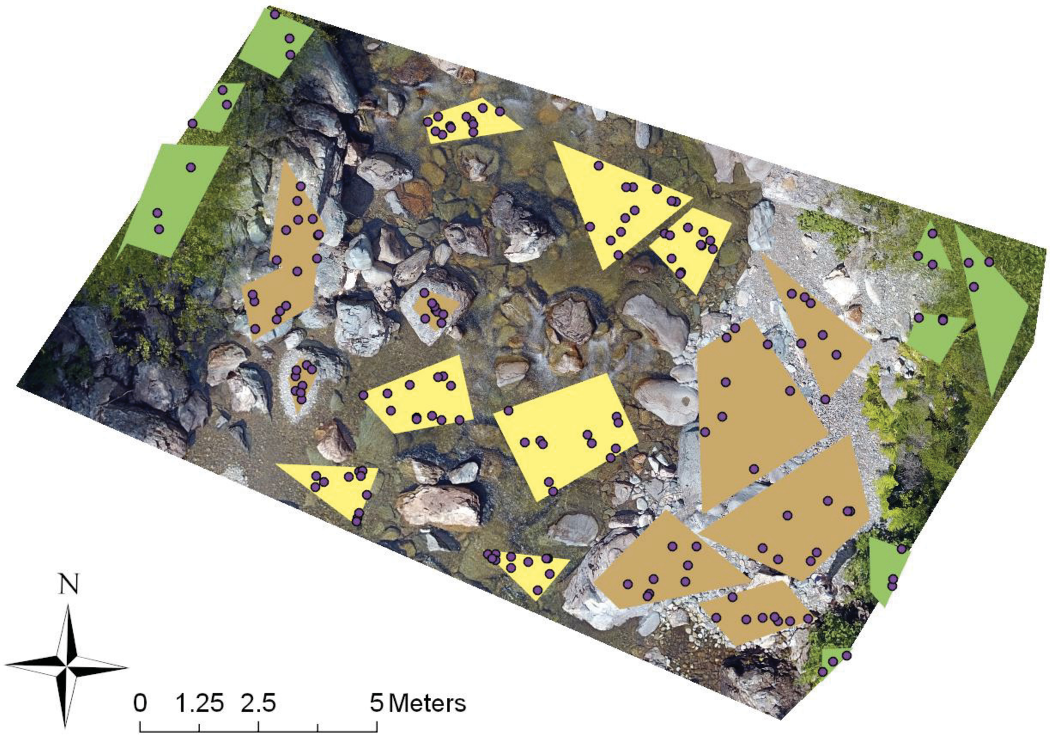

Figure 8: Example from transect 3 of random point selection chosen by the ArcGIS toolset within the training areas used to produce the error matrix. The accuracy point is omitted from training and their predicted value compared to the polygon designation. Green polygons are vegetation, brown polygons are dry substrate and yellow polygons are the submerged substrate.

Using the randomly assigned points within the training sites (Fig. 8) allowed predictions to be made for dry, wet, and RV categories for each transect. When compared to visual assessment the average accuracy of all 7 transects (% agreement between categories) was 90%, with no values lower than 74.7% (Table 2). The highest accuracy was in transects 5, 3, 4 and 1, representing transects in riffle, run/riffle, pool/run and pool/riffle respectively, with each transect scoring above 96% accuracy. The lowest accuracy was in transects 7, 2 and 6, representing transects in the southern most site, pool and run respectively, with transects scoring between 74.7% and 89.4%

accuracy. These results indicate that regardless of river habitat, the imagery was able to adequately separate emerged and submerged substrate and RV with an accuracy of at least 75%, but in most cases exceeding 90%.

Table 2: Overall accuracy of the supervised classification for segmentation transects 1-7, which is the percent agreement between categories in the accuracy points and classified image.

Transect	Overall Accuracy
1	96%
2	78.5%
3	97.1%
4	96.7%
5	98.6%
6	89.4%
7	74.7%

2.3.2 Spawning Habitat

After supervised classification was used to separate larger habitat division (wet and dry), OBIA allowed delineation of texture. Most of the substrate consisted of a range from fine gravel to boulders (Fig. 9). The end member categories of bedrock and silt were represented only in transects 1 and 7 respectively. Underwater vegetation, appearing as green moss was also only represented in transect 7, categorized as "other vegetation". Two of the transects (2 and 6) had shadows across part of the transect which caused misclassification of the submerged and dry substrate but did not noticeably affect the substrate classification (see below for accuracy assessment). Transect 1, near the Forks, had very little small substrate in the dry portion of the transect, therefore boulders, large gravel and gravel had to be combined (Fig. 10). Consequently, as fine gravel could not be separated from the other small substrate, none of the dry transect was considered to be ideal substrate. Of the submerged portion of the transect, 16% was ideal spawning grounds, leading to a total of 8% of transect 1 as ideal spawning substrate (Fig. 10.1). On transect 2, very close to transect 1, large boulders were also present, but the substrate was dominated by sand and gravel, as might be expected in the quieter waters of a pool. Thus, a total of 34% was ideal substrate in both the dry and submerged areas (Fig. 10.2). Transect 3 was similar to transect 1 with a dominance of large substrate especially in the dry portion. It included a total of 17.5% area categorized as ideal spawning substrate with 6% in the dry area and 29% in the submerged area (Fig. 10.3). Transect 4 consisted mostly of boulders and large gravel, similar in wet and dry areas, and contained 11.5% of ideal spawning grounds, 14% in the dry area and 9 % in the submerged (Fig. 10.4). Transect 5 although close to transect 4 was dominated by gravel in the submerged area, but by boulders in the dry habitat. It contained 4% total ideal spawning substrate with none in the submerged area and 8% in the dry area (Fig. 10.5). On both transects 4 and 5, despite the presence of gravel, the substrate was too coarse for abundant spawning habitat. Transect 6 was dominated by large gravel and boulders in both wet and dry areas, and thus only 2.5% of the area was determined to be ideal substrate, with none in the submerged and 5% in the dry area (Fig. 10.6). Transect 7 is furthest downstream where there are depositional areas and the river broadens. It was the only transect with silt. It was interesting that suitable spawning substrate was only present in dry areas. Based on this difference it contained 21% overall ideal substrate with 42% in the dry area (Fig. 10.7).

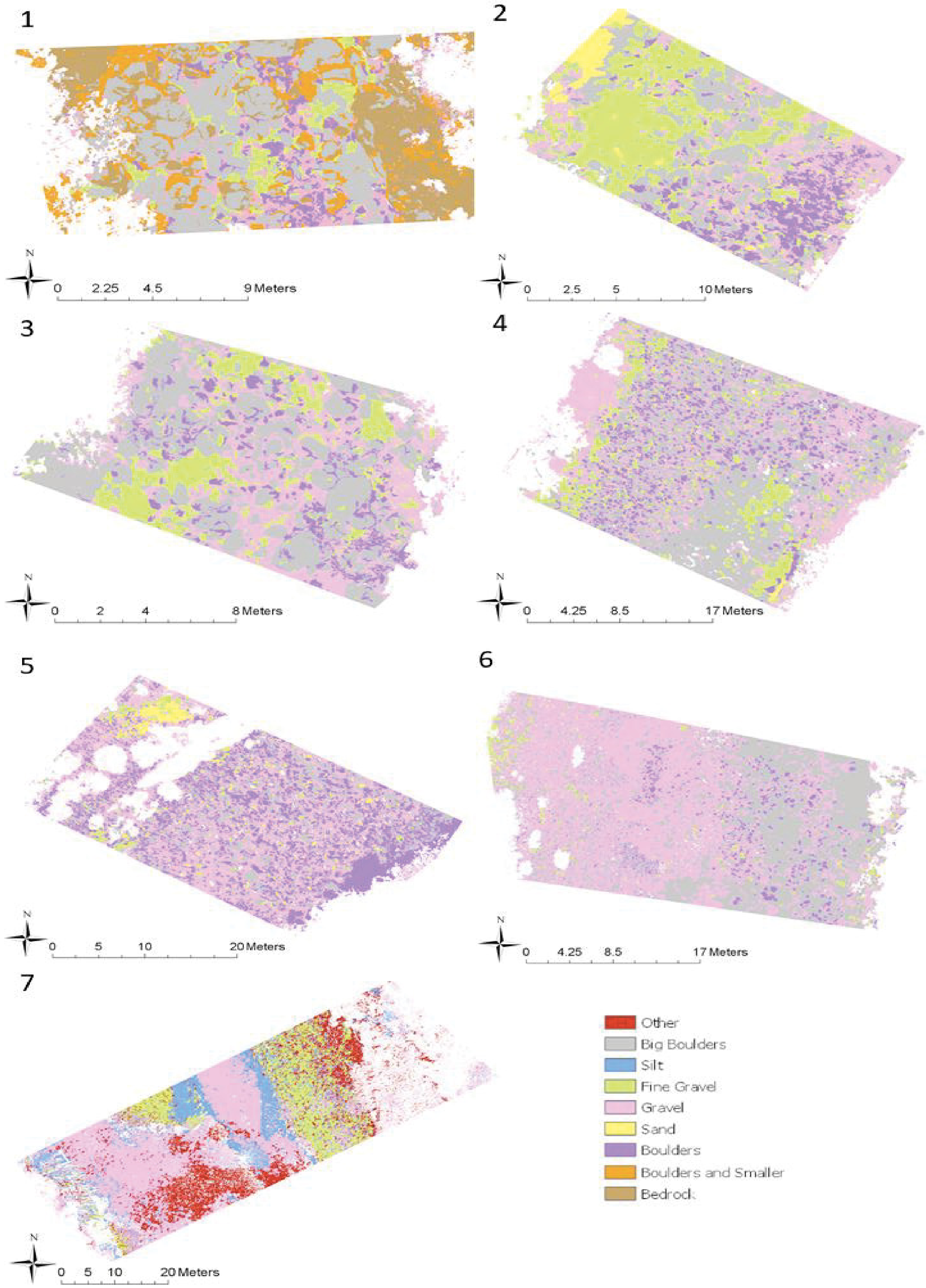

Figure 9: Substrate size of transects 1-7 classified through OBIA. Substrate size includes "other" on transect 7 for submerged vegetation and "boulder and smaller" on transect 1 where small substrate was limited. Submerged and dry substrate are analyzed separately but presented together for ease of analysis.

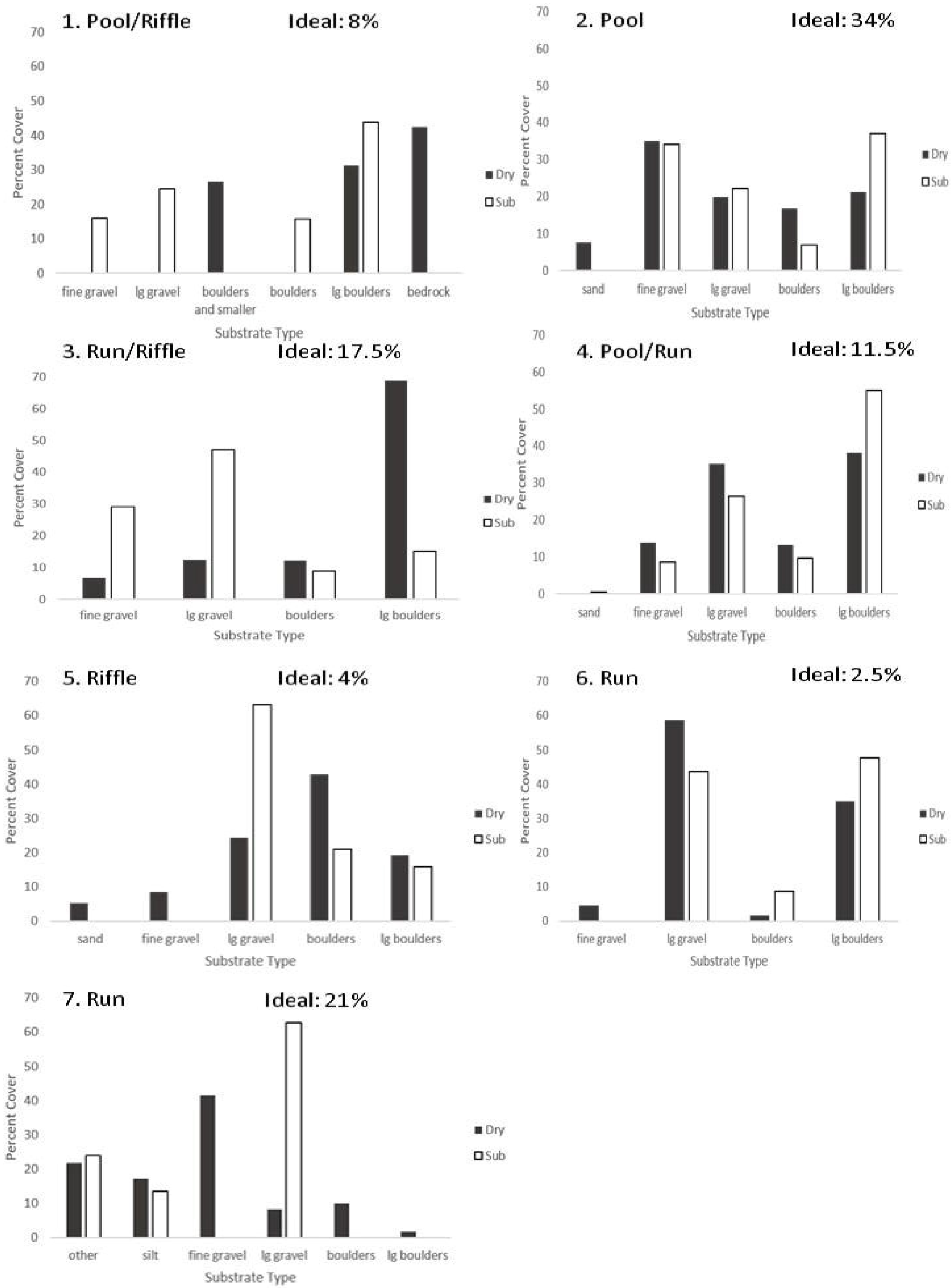

Figure 10: Object-based image analysis results for transects 1-7 on both submerged and dry portions of the river, presented in percent coverage, along with the percent of ideal substrate on each transect. Dry and submerged are processed separately and % are calculated based on individual (dry or submerged) segments but presented together for comparison. Ideal substrate is the total amount of fine gravel found in the combined dry and submerged portions of the transect.

2.3.2.1 Accuracy Assessment: Substrate Texture

Dry and Submerged substrate were identified as either silt, sand, fine gravel, large gravel, boulders, large boulders, bedrock or other vegetation with an overall accuracy of 79% for the dry substrate and 86% for the submerged substrate (Table 3). Over most of the transects, submerged substrate categorization had a higher accuracy than dry substrate categorization, with submerged substrate on transect 7 categorized with complete accuracy. Only on transect 1 (pool/riffle), did the dry substrate have a higher accuracy than the submerged substrate. Within the dry substrate the highest accuracy was on transects 6 (Run), and 3 (run/riffle), and the lowest accuracy was on transects 5 (riffle) and 4 (pool/run). The transect with the highest submerged substrate accuracy was 7 (run) and 6 (run), with transects 3 (run/riffle), 1 (pool/riffle) and 5 (riffle) having the lowest accuracy.

Table 3: Accuracy assessment conducted on the object-based imagine analysis of transects 1-7 for both dry and submerged substrate.

Transects		Overall Accuracy (%)
1 Pool/Riffle	Dry	80.30
	Submerged	75
2 Pool	Dry	79.25
	Submerged	85.71
3 Run/Riffle	Dry	82.34
	Submerged	74.29
4 Pool/Riffle	Dry	78.38
	Submerged	87.18
5 Riffle	Dry	72.73
	Submerged	75.61
6 Run Long-Term Monitoring Site	Dry	82.5
	Submerged	95
7 Run	Dry	78.85
	Submerged	100

2.3.3 Groundtruth Data

An assessment was conducted to compare the groundtruth data to the PCI analysis for transect 1. In this comparison, 75% of the substrate sizes matched between the two analyses. The most noticeable misclassification was that 12% of the groundtruth points were classified as large boulders while classified as boulders in the PCI analysis, with ~96% of this misclassification occurring in the submerged substrate. The 4% of the misclassification within the dry substrate occurred in areas where tree branches obscured the imagery.

2.4 DISCUSSION

Pools, riffles, and runs have long been used as descriptive classifications within rivers in fluvial morphology (Allan & Castillo, 2007) and biological studies (Cunjak, 1988). Descriptions vary in literature, with use of visual assessments or unstated criteria (Jowett, 1993) and removal of runs as a category in some studies (Montgomery et al., 1999). These macrohabitat classifications are used to assess juvenile salmon habitat (Rimmer & Paim, 1983), as well as partition rivers for sampling, with the assumption that physical conditions within classes are similar (Jowett, 1993). The results of this study indicate that the substrate distribution within the macrohabitat designation is highly variable. In addition, the transects do not represent consistent substrate mixes for regions of the river since adjacent transects were also highly variable in composition. Although many studies agree that substrate is a vital component in salmon habitat (Armstrong et al., 2003), there are surprisingly few studies focused on river substrate classification methods using UAV, nor at fine spatial scales, with most methods relying on small scale in-situ surveys. The available studies have focused more on general feasibility and not on how varying physical characteristics may affect the accuracy of the results (Arif et al., 2017; Danhoff & Huckins, 2020). These details are critical in accurately understanding the distribution of fish habitat.

The drone was not used to classify the distribution of riffles, runs, and pools on the river either by visual or image analysis methods. While this might be feasible, examination of riffle areas as spawning habitat (Malcolm et al. 2004) may be inaccurate since substrate variation is so prevalent within the macrohabitats. Instead, a combination of substrate, flow, and slope is used in subsequent analysis (Chapter 3) to more broadly evaluate suitable spawning habitat. River restoration efforts work with a template of idealize spawning macrohabitat, but both substrate and riverbank morphology are controlled (Van Zyll De Jong et al., 1997). In wild rivers, my results suggest that the relationship of riffle/run designation to the location of redds is less certain.

2.4.1 Object Analysis

The submerged substrate classification had an overall higher accuracy than the dry substrate classification, with the exception of the pool/riffle and run/riffle transects. Due to the depth of pools and ripples on the surface of riffles, both were a concern for accuracy. Refraction was also a concern and is discussed below. To limit these effects, the drone was flown during times of low flow, as suggested by Lane (2000). The Upper Salmon River has very clear water as expected of its coarse substrate, with the riverbed being visible even in deeper water. These coupled factors mitigated the effects of pools, with only areas of riffles affecting accuracy (see below). Although this may have improved the accuracy of the submerged substrate, other factors caused a lower accuracy for the dry substrate, explored further below in terms of challenges for image analysis related to specific transects. As many of the transects had similar features, only those with unique features or low accuracy are explored.

2.4.1.1 Effects of Macrohabitat on Classification Accuracy

Although transect 1 ran through a transition zone of a riffle and a pool, both of which are areas that could limit visibility of substrate, the analysis was still conducted with a 75 % accuracy. When comparing the raw RGB image (Fig. 6) to the classified substrate image (Fig. 9), it is evident that neither the riffled water nor the depth of the water obscured the image significantly. Areas of shade seemed to have the most effect on the classification, with some areas of substrate being misclassified as large gravel. In the transition zone at the tail end of a riffle, there were more large boulders rather than gravel, which matches that expected in a riffle, as smaller substrate would have difficulties being retained in high water flow areas (Jowett, 1993).

Most issues in accuracy for both the dry and submerged transects stemmed from lack of training sites. As the transects covered relatively small areas of the river, the substrate that was less common within the transect limited selection of appropriate training sites. The dry portion of the pool/riffle transect 1 had very little of the smaller substrate. To have a large enough sample size for both the training and accuracy segments, all substrate below the large boulder class had to grouped. This caused a reduction in the number of classes. The reduction correlated with an increase in accuracy of the transect. The accuracy may have been affected by the decrease in classes as the OBIA would have been less complex and therefore had larger thresholds for the pixel analysis. But this is not always desirable when aggregation of classes would obscure subtle changes in habitat distribution. When analyzing substrate, classes that serve different functions such as spawning suitability cannot be grouped.

Riffle areas have the potential to be ideal spawning habitat, owing to swift flowing water, aeration and availability of small substrate (Coulombe-Pontbriand & Lapointe, 2004; Fitzsimons et al., 2013). In the submerged classification of transect 3 run/riffle, there were patches of fine gravel in both the northeast and southwest areas that would have higher water flow and smaller substrate, both characteristics of potential salmon spawning grounds (Armstrong et al, 2003). The classification had the lowest accuracy of the submerged transects (74.29%). Since all three transects through riffles had lower accuracy, it is reasonable that this results from turbulence at the water surface of the riffles. The sub-classifications with the most overlap/error at this transect were boulders and large boulders, commonly in riffles, suggesting that the distortion at the water surface may have led to confusion error in OBIA. Arif et al (2017) used similar methods to analyze substrate from UAV imagery and found that the larger grain sizes resulted in a higher number of misclassifications. They concluded that altering texture layers could help mitigate this problem, without identifying the underlying cause. Casual examination of the images suggests that more turbulent sections of riffles had reduced accuracy compared to flatter water. We note that increased error at this large substrate size has minimal impact on the assessment of smaller substrate, such as the fine gravel, important in salmon spawning habitat.

Transect 7 through the run was situated in the southernmost site, the only one containing silt/mud, and submerged vegetation. The submerged area was difficult to assign training sites, as the silt/mud and other vegetation looked murky in the water on the RGB images. Although this may have seemed problematic to visual inspection, it had a 100% accuracy in PCI, because there were only two classes both expressing distinctive textures. This allowed the software to extract data that was more difficult to designate on the RGB images. Lacking the depth of the pools and the visual distortions of the riffles, the run transects had a higher accuracy.

2.4.2 Spawning Grounds.

The preferred substrate size for Atlantic salmon spawning reported in the literature ranges from gravel as fine as 0.54 cm to as large as 10 cm (Armstrong et al., 2003). In the current study, ideal spawning substrate was based on the classifications assessed with object-based image analysis, with fine gravel (2 mm-5cm). The pool transect (2) had the largest area of ideal spawning ground (34%), as well as the highest amount of sand. Pools are characterized by deeper water and slower currents, and the low flow in these areas leads to sedimentation of smaller substrates (Jowett, 1993). However, low flow and finer sediment may also signify lower aeration in the substrate which can affect the survival rate of eggs (Lapointe et al., 2004). Redd digging behaviour in salmon aids in the removal of smaller sediments to increase oxygen to the eggs (Everest et al., 1987), but salmon also prefer higher water velocity of 31-55 cm s^{-1} (Gibson, 1993), characteristically occurring in runs (Jowett, 1993). Although pools may contain the largest relative areas of ideal substrate, low flow/aeration makes them less suitable for spawning. Transition zones at the downstream end of the pools (pool/run, pool/riffle), can lead to higher water velocity at the tail end of the pool while maintaining smaller substrate deposits. These areas have been linked to spawning (Malcolm et al., 2004) and are constructed for this purpose in river restoration (Payne & Lapointe, 1997). Runs are characterized by shallow, swift water that does not break at the surface (Jowett, 1993), but are variable in water velocity and substrate size. Among the transects in this study, ideal spawning substrate (fine gravel) comprised 21% of total available substrate at on the long-term monitoring site (transect 7), and 2.5% of total available substrate in the other run, transect 6. Although transect 6 did not have much fine gravel, it contained abundant large gravel. Salmon are able to spawn in larger substrate when other factors suit their needs (Gibson, 1993), such that among substrate and flow, runs contain many suitable variables for spawning habitat (Armstrong et al., 2003). Runs have also been linked to overwintering habitat of juvenile salmon (Cunjak, 1988), creating vital habitat for the salmon at other life stages.

Riffles tend to have faster currents and are often characterized visually by a broken water surface (Jowett, 1993). Riffle transect 5 had mostly large gravel and boulders and very little ideal spawning habitat. Transect 3 had abundant large boulders, but also small patches of finer sediment typically located behind large protruding rocks, caused by a lower flow and settlement of smaller grain sizes. This resulted in an average of 17.5% of ideal spawning habitat. In the literature, riffles are considered to have good potential spawning characteristics (Malcolm et al., 2004). Although runs have the potential to be spawning habitat, not much is written linking runs or pools, with studies referencing riffle and pool/riffle transition zones (Fitzsimons et al., 2013).

As stated above, transition zones between riffles/runs and pools also allow for a decrease in flow and so the settling of smaller substrate. Although riffles may not be as suitable for spawning as transition zones, a study by Bagliniere & Champigneulle (1986) determined that they were very productive locations for juvenile salmon, even compared to runs.

2.4.3 Groundtruth Data

An original goal of this study was to determine the accuracy of the analysis, this included observing how substrate size may be skewed by refraction caused from the water. The assumption was that refraction might cause the substrate to appear larger. Unexpectedly, all the misclassified substrate points were designated as smaller in drone images than in groundtruthing. These points were in areas of deeper water, where it may have been more difficult to measure the substrate due to depth and current. Although this does not signify that there was no refraction, it shows that the refraction was not significant enough to increase the substrate size class at these depths.

In terms of salmon spawning habitat, two sources of uncertainty occur in this study. First, visual designation of gravel classes from orthomosaics would benefit from the greater precision of physical measurements. This approach applied to transect 1 provided reasonable accuracy. Because the training points used in the other transects arose from the orthomosaics, misclassification in the gravel classes is an unknown. However, visual designation provided a consistent basis for gravel separation judged by the ability of OBIA to apply these designations. Secondly, a single substrate threshold was used for the delineation of spawning habitat. Ideal substrate for spawning is likely not constant but was applied consistently among the transects and thus functions as a relative definition within this study.

It is useful to compare the feasibility of both drone and ground team survey methods. The drone was able to cover all 7 transects within 2 days, the foot travel between locations taking the most time. Two people can easily complete the drone survey, an extra person mostly due to wilderness safety concerns and avoiding river landings by the drone. Physical groundtruthing took much longer to complete, one day for each transect. In contrast, the image analysis took much more time to complete, and was largely dependent on computing power. Although both physical survey and remote sensing methods are valid, exploration into the object-based image analysis using UAV's would allow for larger sections of rivers to be surveyed with higher accuracy and in shorter periods of time. These broad-scale substrate analyses could then be used to determine breeding potential of rivers or to analyze for restoration such as is currently being conducted in Norway, where substrate is being manipulated to increase salmon habitat (Fjellheim et al., 2003) as well as in North America (Mitchell et al., 1998). It could also allow for further studies to be conducted, such as the shifts in substrate after large rainstorms or ice events. Seeing where ice is forming and on what substrate could also allow for a better understanding of how salmon are sheltering in the rivers during the winter (Linnansaari et al., 2009).

2.4.4 Application

Habitat degradation is a serious threat to the river productivity, affecting all life stages of the *Salmo salar* and other salmonids (Einum et al., 2008). Recent efforts, including those in Norway and North America, have sought to increase salmon habitat by large scale manipulation of substrate (Fjellheim et al., 2003; Têtu et al., 2016; Emerson, 2014). Although substrate is a vital component of spawning habitat (Armstrong et al., 2003), it can also increase the fitness of other life stages, including prey availability (Mitchell et al., 1998). Van Zyll De Jong et al (1997) suggested that the most effective way to increase the density of juvenile salmon was by manipulating substrate clusters and adding boulders. Current salmon habitat studies often utilize on-ground sampling of the river, relying on observational data and photographs (Moir et al., 2009; Malcolm et al., 2004; Louhi et al., 2008). Although UAVs have become more popular in recent years, very few studies have looked at their potential for substrate analysis in rivers for biological study (Arif et al., 2017). Based on my results, they emerge as a powerful tool in river mapping, especially effective in otherwise inaccessible terrain.

This study demonstrated that diversity in substrate within macrohabitat lessens the value of this coarse traditional classification in categorizing spawning habitat. It also identified visibility issues in the broken water surface of the riffles as sources of inaccuracy for object-based image analysis. At the same time, substrate alone does not determine spawning habitat. Pool transect 1 had by far the highest amount of ideal spawning substrate, but other conditions in pools such as flow subtract from suitability indicated by substrate. River bottom texture should be viewed as a starting point for assessing habitat suitability, adding other data layers to better quantify spawning habitat as I undertake in the following chapter.

2.5 CONCLUSION

This study has shown that substrate analysis on UAV-derived orthomosaics are possible despite the issues surrounding the collection of riverbed imagery through water. Pools, riffles and runs all had relatively high accuracies, the breaks in the river surface of riffles proved to have the highest impact on accuracy, with water depth within pools not substantially affecting accuracy. Although such analyses are possible using groundtruthing methods, the time needed in the field to gather the same amount of data is substantially less using a UAV. With a now established method for the object-based image analysis, the process within the laboratory could be streamlined to be more efficient, reducing the time needed for the substrate analysis. In conclusion due to the relatively high accuracy of the transects, the ease of use and speed of the UAV, this is an appropriate method in which to conduct substrate classification. The results can further be used to conduct preliminary analysis of suitable substrate for salmon spawning, or in subsequent species distribution model analyses to map potential spawning habitat.

CHAPTER 3 3D MAPPING AND ANALYSIS OF RIVER HABITAT FOR ATLANTIC SALMON CONSERVATION IN THE INNER BAY OF FUNDY

3.1 INTRODUCTION

The use of river habitats by fish is a complex topic because highly mobile species use a diversity of different microhabitats within the river. There is ample evidence that habitat diversity is important to fish life history as different life stages have different habitat requirements (Armstrong et al., 2003). The different levels of complexity found in rivers have allowed for the evolution of fish to take advantage of different habitats within the same river (Gorman & Karr, 1978). Different areas of the river are also used for different life stages, with each stage requiring a different set of environmental variables. Atlantic salmon (*Salmo salar)* parr, for example, tend to choose coarser substrate than their smaller fry counterparts (Hedger et al., 2006). In the absence of older salmon, fry will exploit higher velocity waters, due to their increase in food availability (Höjesjö et al., 2016). In the presence of older salmon, fry will retreat to slower flowing, coarser habitat, due to intraspecific competition and predation. This change in habitat use can also be observed seasonally, with juvenile salmon within Norwegian rivers displaying seasonal variations in habitat use caused by fluctuations in water flow and temperatures (Heggenes & Saltveit, 1990). The high variability found in river habitat can help facilitate the survival of juveniles.

Habitat variability has also been found to alter behavioural and growth changes in fish, such as with Atlantic salmon in both wild populations (Finstad et al, 2007) and hatchery reared fish (Brown & Laland, 2001). In wild fish, when stream complexity was decreased, fish were observed to alter daytime sheltering behaviour, and showed an overall decrease in body mass (Finstad et al, 2007). Similarly, hatchery reared fish raised in high densities with low structural complexity environments, have altered behaviours that lead to decreases in food conversion efficiency and growth (Brockmark et al. 2007).

Wild salmon are archetypal river species, important for recreation fisheries, food, and ceremonial uses including in First Nations practices. Moreover, Atlantic salmon have a role in linking marine and freshwater environments through their migration (Jonsson & Jonsson, 2003). Wild Atlantic salmon populations have been declining throughout Europe and North America due to pollution, dams and dewatering of streams, as well as other factors at sea (Parrish et al., 1998). Some populations are more affected than others, such as the Inner Bay of Fundy (IBoF) salmon, which were designated as endangered by the Committee on the status of Endangered Wildlife in Canada (COSEWIC) in 2001 (Government of Canada, 2013). Historically they were estimated to have over 40 000 returning adult salmon, but by 1999, their numbers had declined to 500 (Irvine et al., 2005). The IBoF salmon are known to occupy 32 of the 50 rivers located in the Inner Bay of Fundy, their range spanning between the Mispec river in New Brunswick to the Pereaux river in Nova Scotia. Due to large declines in populations, there have been efforts in river restoration and repopulation projects (Einum et al., 2008; Trzcinski et al., 2004). Some of the most recent initiatives have been highly successful, focused on the Upper Salmon River in Fundy National Park, in New Brunswick. These initiatives involve a partnership between Parks Canada, Cooke Aquaculture, Fort Folly First Nation, University of New Brunswick and Dalhousie University, and use the live gene bank program, established by the Department of Fisheries and Oceans (DFO), to re-establish populations of genetically diverse wild salmon (Clarke et al, 2016). Due to logging dams placed in the early 1900s and the deterioration of their fishways, the Upper Salmon River is theorized to be vacant of native populations with returning adults being strays from surrounding rivers (Dadswell, 1968). These returning wild strays, along with Big Salmon River smolt were collected to be reared as broodstock for the Upper Salmon River, allowing for a genetically diverse population to be reintroduced into the river (Clarke et al, 2016). The rearing strategies for the IBoF recovery program, including keeping smolts in marine net pens, led to the finding that juveniles released into rivers before the onset of feeding had higher mass and fecundity than those that were kept in captivity for longer (Clarke et al, 2016), showing the importance of early life history in restocking success.

Freshwater habitat use by Atlantic salmon is characterized by several categories based on life history stage (egg, alevins, fry, parr, smolt and adults). It is important to understand habitat use by these stages so that habitat assessment contains the scale and resolution to delineate them. Fish returning from the ocean to spawn will often traverse the river looking for spawning habitat and resting in holding sites. Spawning habitat selection is then based on physical factors within the river such as depth, water velocity, streambed substratum and cover (Armstrong et al., 2003). The decreasing number of salmon, and increasing number of restoration projects, has led to a need to understand the interactions between the environmental requirements of spawning habitat, helping to determine which rivers have the highest spawning potential. Once spawning habitat is identified, the same methods can be used to determine the requirements of other life history stages such as juvenile habitat.

Species distribution models (SDM) are an approach implemented to understand the spatial dynamics of animal populations in relation to environmental characteristics. They use environmental data layers coupled with presence/absence data to predict species distribution. SDM are particularly important in conservation or restoration efforts, where potential habitat can be mapped or predicted. Although SDM are common in terrestrial and some aquatic environments, they are more difficult to apply in river systems, where spatial environmental data are less commonly available due to fast flow, light penetration, turbidity and refraction (Woodget et al., 2015). Rivers pose other challenges in measuring spatial environmental data including vegetation cover (e.g. trees and shrubs) obscuring aerial remote sensing surveys and accessibility to field sites. However, rapid advancements in remote sensing as a result of unmanned aerial vehicles (UAV) technology, have made river mapping more feasible and accessible (Nex & Remondino, 2014).

The goal of this research is to explore the use of UAV's in creating a SDM of potential Atlantic salmon spawning habitat. My previous work determined that supervised classification could be applied to different types of river habitat (pool, riffle, run) with acceptable accuracy (Chapter 2). This chapter will explore the construction and results of an SDM through the following objectives:

- Test the utility of UAV remote sensing for the creation of a DEM and extraction of spatially continuous environmental data sets for subsequent use in mapping IBoF salmon spawning habitat.

- Assess the use of UAV derived environmental layers in creating an SDM of potential salmon spawning habitat through accuracy analysis of both the environmental layers and the SDM.
- Evaluate the results of the SDM by comparing them to known salmon spawning preferences.

3.2 MATERIALS AND METHODS

3.2.1 Study Site

Located in the Bay of Fundy, the Upper Salmon River (USR) drains into Chignecto Bay near Alma, New Brunswick. It is considered by the Department of Fisheries and Oceans Canada (2010) to be critical salmon habitat. The river descends from a plateau to the sea through the protected wilderness of the park. Salmon habitat ranges from the estuary with a salt marsh and a macrotidal delta near the mouth of the river, to two large falls at either end of the "Forks" (a fork in the river), which they cannot cross (Fig. 11).

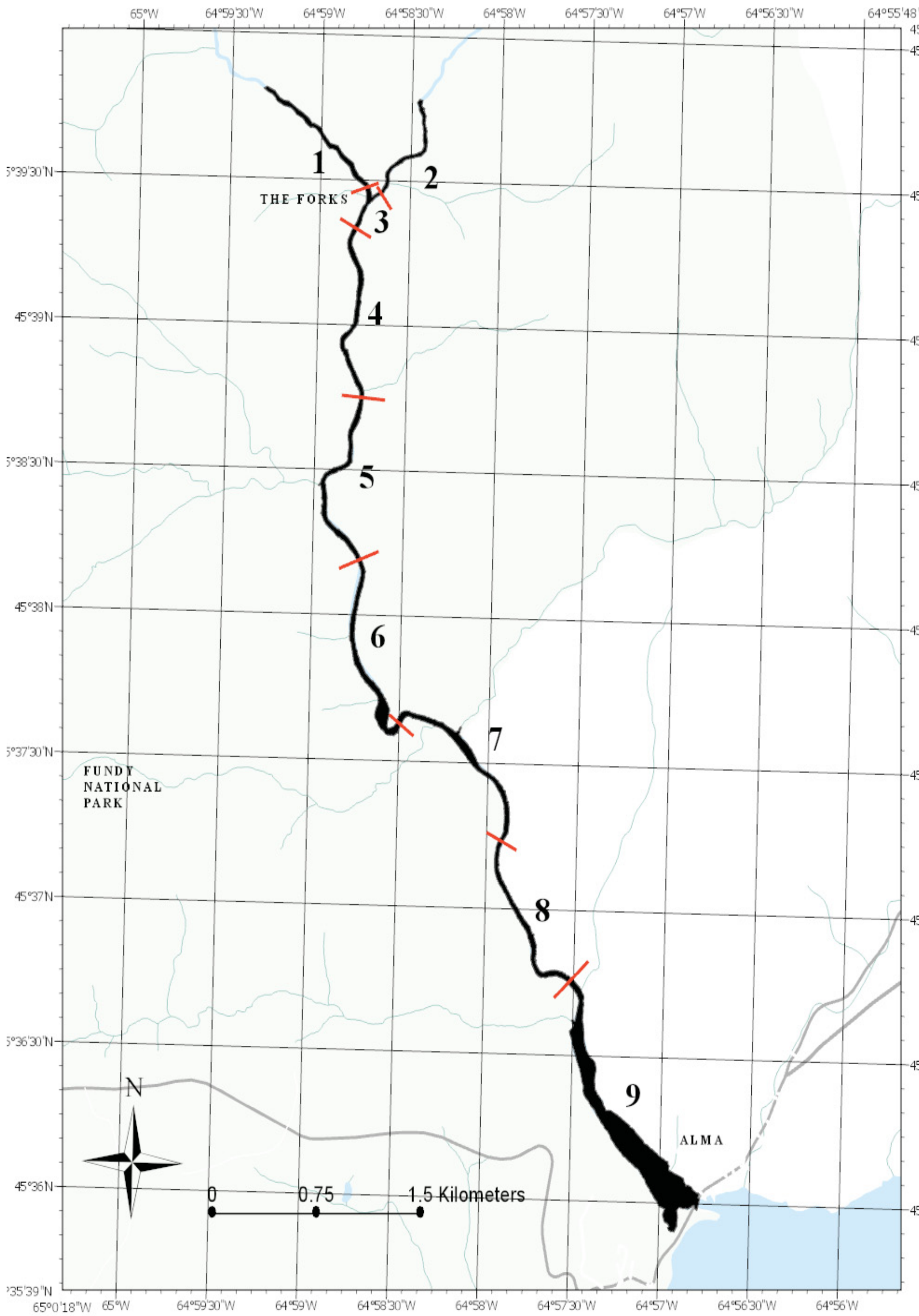

Figure 11: Map of the Upper Salmon River within New Brunswick. The solid black line depicts the extent of the study site, from the mouth of the river and ending at Match Factory Falls on the east side and Laverty Falls on the west side. The red lines show the 9 subsections of the river used in Pix4D to construct the DEM.

3.2.2 Data Collection

3.2.2.1 Spawning Salmon

IBoF salmon tagging data was provided from a post-release movement pattern and behaviour study. It tracked adult salmon, reared in captivity from smolt to maturity, after their release into the USR. Fish were tagged through surgically implanted (2015 & 2016) or externally attached (2017) MCFT2 coded radio tags from LOTEK Wireless Fish & Wildlife Monitoring (Samways, 2017). The anesthetic used was clove oil at a dosage of 50 – 70 ppm. Once in the anesthetic, fish were timed to ensure they were properly anesthetized within 2 minutes. During the procedure, which took 2-3 minutes, water was passed over their gills to ensure they did not suffocate. Fish were then placed in an oxygenated recovery tank. Fish were released in 2015, 2016 and 2017. Tags were detected using a portable receiver by hiking the 10 km salmon accessible extent of the USR. Fish were deemed "in place" when antenna were perpendicular to the river and the signal strength reached its maximum. GPS (global positioning system) locations were then recorded from the riverbank. GPS points were mapped over orthomosaics to manually correct for any potential discrepancies in location and sorted by spawning habitat or holding habitat. The fish was assumed to be spawning if the location aligned with preferred habitat based on substrate and estimate flow, as well as known spawning locations. Salmon were not counted as spawning until November 10 as this was considered to be the earliest spawning time. If the location was determined to be in a low flow riffle or a run, they were considered to be spawning, but fish observed within a pool, were considered to be in holding. As salmon will often build practice redds in spawning habitat while traveling up and down the river, individual tagged salmon could be counted as spawning on more than one occasion if on subsequent weeks were found in suitable spawning habitat. Although these do not represent guaranteed spawning locations, they were more likely spawning based on substrate, water flow and known spawning locations. After December 21, fish were considered to have completed spawning. Tracking data were provided for 2015, 2016 and 2017. A total of 305 fish were observed over 10 km of the river. Only the spawning presence data was used in the species distribution model.

3.2.2.2 Drone and Pix4D

A DJI Phantom 4 drone was used to obtain imagery of the Upper Salmon River during the fall of 2016, during a relatively low stage of river flow, in late August. The standard high dynamic range and high definition camera found on the DJI Phantom 4 drone was used. Drone positioning was calculated using the barometric pressure sensor for elevation and the on-board GPS/GLONASS (global navigation satellite system), with altitude corrected later using manual tie-in points in Pix4D from available LiDAR data. Approximately 5501 images were taken with ~80% overlap in the imagery, spanning the length of the salmon habitat range in the river. As riverbank varied in height due to trees, large rocks and cliffs, imagery was collected at 40 meters in height in 7 second intervals. In areas where trees and cliff height did not allow for the drone to be flown at 40 meters, a separate flight was also done at 60 meters. These flights only encompassed the top of the trees and were precluded from Pix4D if coverage for the river was over 80%, as well as were removed from the analysis in proceeding steps as only the riverbed was analyzed. Flights were also done at 30 meters and video was taken for extra data, but these were precluded from Pix4D. As suggested by Pix4D, flight heights did not differ by more than a factor of 2. In order to process the data efficiently, photos were separated into 9 sections processed through Pix4D to produce orthomosaics and digital elevation models (DEM). The latter were constructed through structure from motion, which utilizes corresponding features in overlapping imaging to create a three-dimensional model of the terrain using photogrammetry (Chelsey et al., 2017; Burns & Delparte, 2017).

3.2.3 Processing

In order to prepare the DEM for further analysis, data were condensed for manageability via a set of transformations to convert from 1.74 cm per pixel resolution and 32-bit float data to a resolution of 3.48 cm per pixel and 16-bit signed data (Fig. 12). This was a required step as the large size of the data prevented it from running through the software. The transformations included an aggregate conversion, which combined cells in grids of 4 (2 by 2 pixels), using the mean value to represent the whole area. Starting with high resolution, a reduction to this extent was not considered to affect the accuracy of the subsequent analyses. The DEM was clipped to remove as much of the forest vegetation as possible, since vegetation was not considered as a factor in the environmental layers.

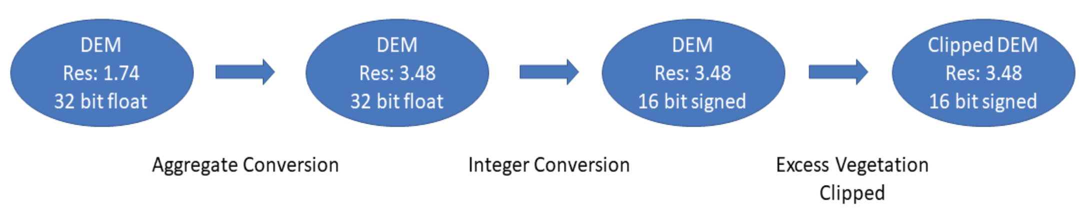

Figure 12: The transformations undergone by the DEM in post-processing.

3.2.3.1 Slope

Slope was calculated in ArcGIS using the Slope Tool from the DEM which uses a moving window, with 3 by 3 cells. The output of the raster was in degrees, with values ranging from 0-90. The maximum rate of change was calculated using a planar slope algorithm taking into account the heights of the surrounding eight cells and the steepest descent. Slope was calculated and coded into each individual cell to create a continuous data raster layer, which was then converted into ASCII (American Standard Code for Information), the required format for MaxEnt (see below). Although slope is in degrees for MaxEnt, for ease of assessment it is presented as meters over distance.

3.2.3.2 Water Flow

Water velocity is considered to be an important factor in salmon spawning habitat but modeling this variable can be complicated for river habitats, since flow changes based on rain and snow events and salmon have a spawning season that lasts multiple months. Without a water input value, which was not available, water velocity could not be modelling. This layer was thus modelled in ArcGIS pro as patterns in water flow using a scale from slow (low accumulation) to fast (high accumulation) (see below). Since the result is to be used for SDM built in MaxEnt (see below), which concentrates on environmental patterns rather than number ranges, this classification approach was sufficient. Flow was modelled in a grid format by calculating water direction, accumulation and slope.

The DEM was first processed through a Sink Spatial Analyst Tool available in ArcGIS, which determines all the sinks (cells with no drainage direction) caused when all the surrounding cells are higher or when two cells cause a loop by flowing into each other. The Fill Spatial Analyst Tool was used to fill all the sinks on the grid as well as repair any discontiguous paths. If the sinks were not filled, there could be gaps in the drainage network affecting the subsequent steps. The sink filled DEM raster was then processed through a Flow Direction Spatial Analyst Tool available in ArcGIS which creates a raster showing the direction water will flow based on neighbouring cells and slope (or elevation raster), following the direction of steepest descent. The resulting raster is coded with values that indicate flow direction from every cell into its neighbours, identifying channels within the river, and taking into consideration the width of these channels. The Flow Accumulation Tool available in ArcGIS was then used, which takes into account the fine scale of the DEM, slope, and flow direction, which results in a coded raster of flow, which was then converted into ASCII, the required format for MaxEnt (see below). Cells with a flow accumulation of 0 had no flow into them and were located on ridges or rocks protruding from the water. Low accumulation cells had less cells draining into them and so a slower flow. Cells that had a higher accumulation value had a more concentrated flow, this included narrow stream channels, where water will flow faster. As water velocity could not be modeled without more data, this approach allowed model generated mapping of water flow patterns to be incorporated. This method is often used to delineate watersheds, natural drainage direction, river order as well as other hydrological uses (Nurhamidah et at., 2018; Sten et al., 2016; Omran et al 2016). To visually assess river flow, it was averaged for each section and graphed according to the linear distance covered by each section. The raster layer contains "paths" through tight channels, where flow is faster, but averaging may skew these values. Since the full raster layer is used in the MaxEnt analysis, this will not affect the results of SDM.

3.2.3.3 Substrate

Substrate is another important factor in spawning habitat, since it must be small enough for salmon to dig redds, but large enough to allow for aeration through the sediment. A substrate raster layer was created using object-based image analysis (Chapter 2). An object-based supervised classification was conducted in ArcGIS to exclude riverbank vegetation, leaving submerged and dry substrate (Fig. 13). The latter was important to consider habitat at higher river flows. Visual inspection of drone images was used to designate dry and wet polygons for training, and training sites were selected along the entire length of the river sections, both in sun and shaded areas.

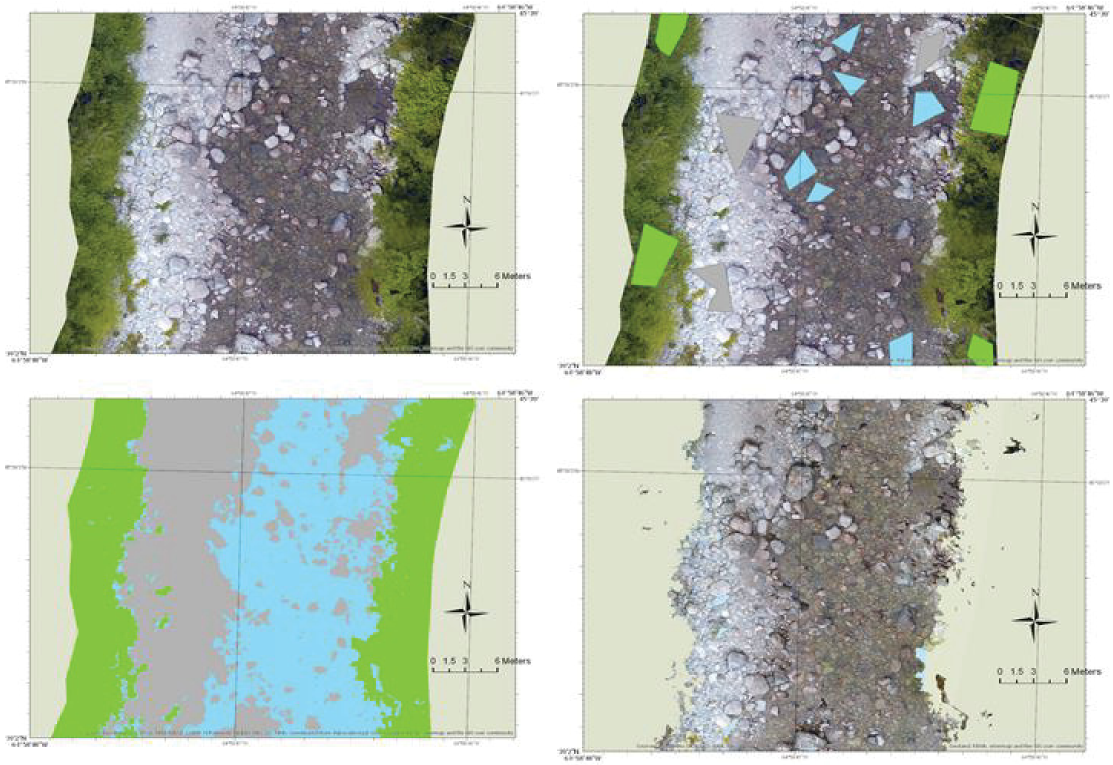

Figure 13: The process of classifying substrate. A. The river orthomosaic segment from drone imagery. B. Training sites are selected with RV (green), dry (gray) and submerged (blue). C. This produces classified shape files which are used to extract dry (gray) and submerged substrate (blue) from the RV (green). D. The resulting RV free raster layer.

A reference dataset of training locations was used as an accuracy assessment for distinguishing wet/dry/vegetated river habitat. Random sampling was used to assign 500 distributed points onto the training sites used in segmentation. An overall percentage agreement was calculated comparing the training sites to the classification. Submerged and dry substrate were imported separately into PCI Geomatics for substrate size analysis. Substrate size initially included silt, sand, fine gravel, gravel, large gravel, boulders, large boulders, and bedrock (Table 4). Large boulders encompassed all substrate larger than 40 cm that was not bedrock. Substrate that had broken off bedrock including rockfalls from riverbank cliffs had the same texture and pixel signature as the bedrock was classified as large boulders. Similarly, gravel and fine gravel were merged since the visual difference between 2mm-2cm and 2cm-5cm were too small to distinguish accurately in the analysis (Table 4).

Table 4: Size classes used to classify substrate in the object-based image analysis

Class	Substrate
1	Silt
2	Sand (0.063-2mm)
3	Fine Gravel (2mm-5cm)
4	Large Gravel (5-20 cm)
5	Boulders (20-40cm)
6	Large Boulders (>40cm)
7	Submerged vegetation

In PCI, an object-based image analysis (OBIA) was conducted to classify the size of the submerged and dry substrate based on Chapter 2. A texture analysis (homogeneity, contrast and mean gray-level values) was used to analyze the red band on 10 x 10 pixels. These layers and band were used based on the suggestions from the 2017 study conducted by Arif et al. which did a preliminary examination of OBIA in river terrain. The image underwent an object-based segmentation based on these textures, and the red band. The software was manually trained and classified into the substrate categories in Table 4 based on visual assessment of the images. The validity of this approach was verified for different river macrohabitats such as riffles and pools (Chapter 2). Each class had a minimum of 50 training sites and 25 separate accuracy sites (see below), except when there were insufficient samples to meet the minimum requirements. The substrate polygons were then exported into ArcGIS and merged into a single raster layer.

One third of all training sites were allocated to an accuracy assessment. An error analysis was constructed between the unused training samples and the classified substrate for each of the nine river sections.

3.2.4 MaxEnt

MaxEnt is an open-source software used to model species distributions. Maximum entropy, referring to information entropy, assumes that every outcome on the model is as likely to occur as another. This concept is used to model species distributions (Harte & Newman, 2014; Philips, Dudík & Schapire, 2017). Through the combination of environmental variables which are geocoded into raster layers, along with species presence data (as GPS coordinates), it creates probability distribution models. This is done by observing the patterns in the environmental layers found at the presence data points. Each grid cell in the output has a predicted habitat suitability ranging from 0-1 with 1 being areas with the best predicted conditions. In this case the presence data represent fish in spawning habitat, and the map will indicate the relative likelihood of spawning habitat occurring in one cell compared to another. The environmental layers for water flow, slope, and substrate, were processed through MaxEnt along with GPS presence data that indicated spawning salmon. In order to validate the model, 20% of the presence locations were set aside for use in the receiver operating characteristic (ROC) curve, which compares the model performance to the results of a theoretical model with a prediction based on random distribution. As correlation between variables can skew their perceived contribution, the permutation importance is calculated, which examines how altering variables within the training data will affect the AUC.

In order to analyze the environemental variables, response curves are created. These show how the predictions created by the model for the probability of presence change as each of the individual environmental variables vary. Each variable is modelled as a cloglog expression, which corresponds to 1-exp(-c*r), where r is the raw model value and c is the predicted ommision rate (true abundance of the species over the model predicted abundance), resulting in an estimate of presence probablity between 0 to 1. This is graphed as a curve (continuous data) or a histogram (categorical data), where the y axis shows the presence probability against the x axis environmental data. It should be noted that flow, slope and substrate are all linked (correlated) variables, which can cause issues in the response curves. The curves are produced by changing one variable in the model, but the response can depend on interactions in ways that are not obviously interpretable in the curves, making the curves skewed, and therefore are analyzed with caution.

3.3 RESULTS

3.3.1 Tracking Data

Out of 305 tracking points collected from 2015 through 2017, 81 were in probable spawning habitat with 224 in probable holding habitat (Fig. 14-16). Within the spawning habitat, 12 of the points were from 2015, 50 were from 2016 and 19 were from 2017. Although holding areas were found within the northernmost sections of the river (section 1 and 2) there were no spawning fish observed there. The highest concentration of spawning fish were located within the mid-section of the river (sections 6-7), with lower concentrations in sections 3, 4, 5, 8 and 9.

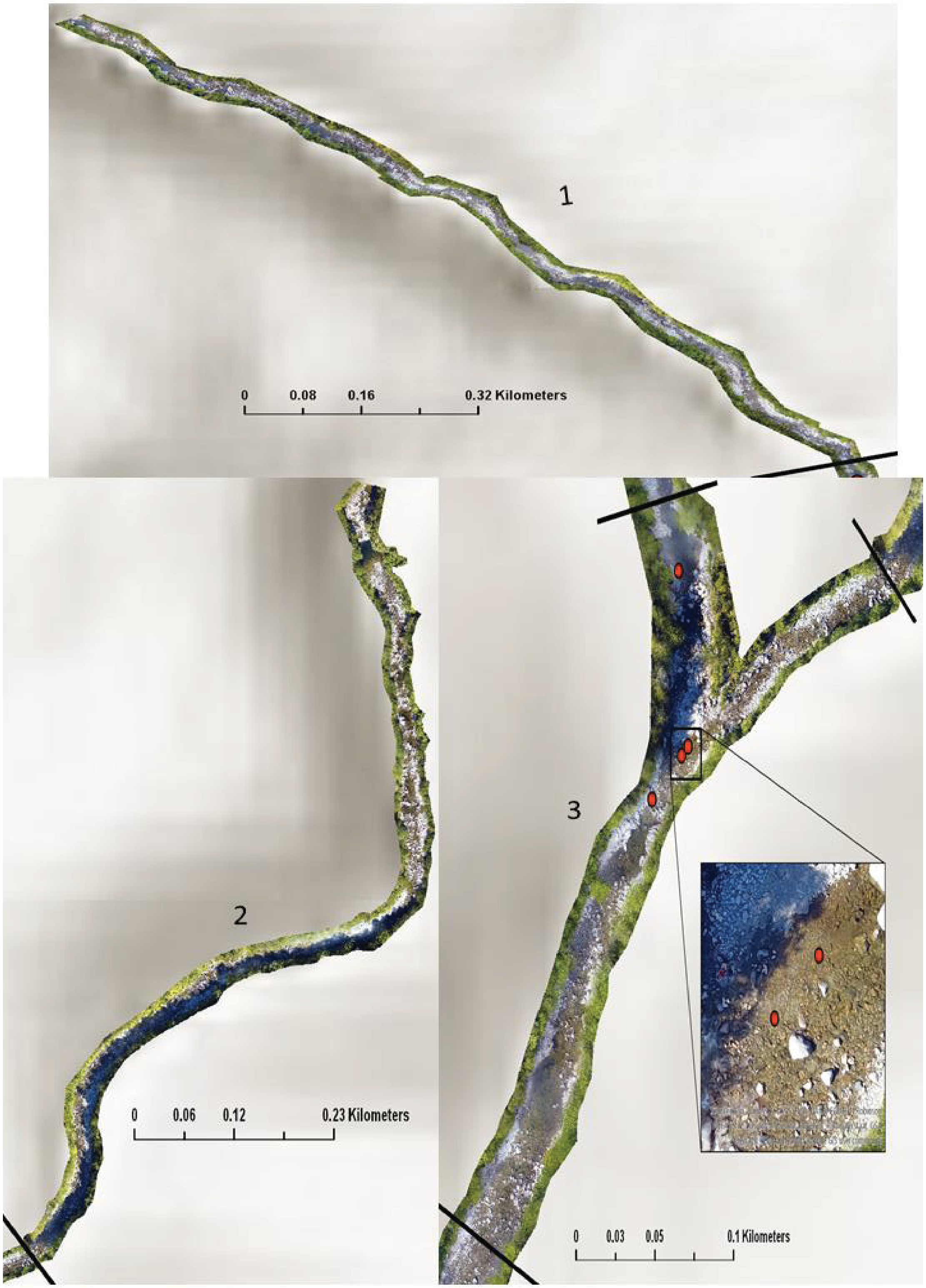

Figure 14: Corrected tracking data showing the GPS locations of the spawning salmon (red) within the Upper Salmon River for 2015-2017, for sections 1-3, mapped on orthomosaics. Black lines mark the division between sections. Insets show areas where clusters of spawning points were located

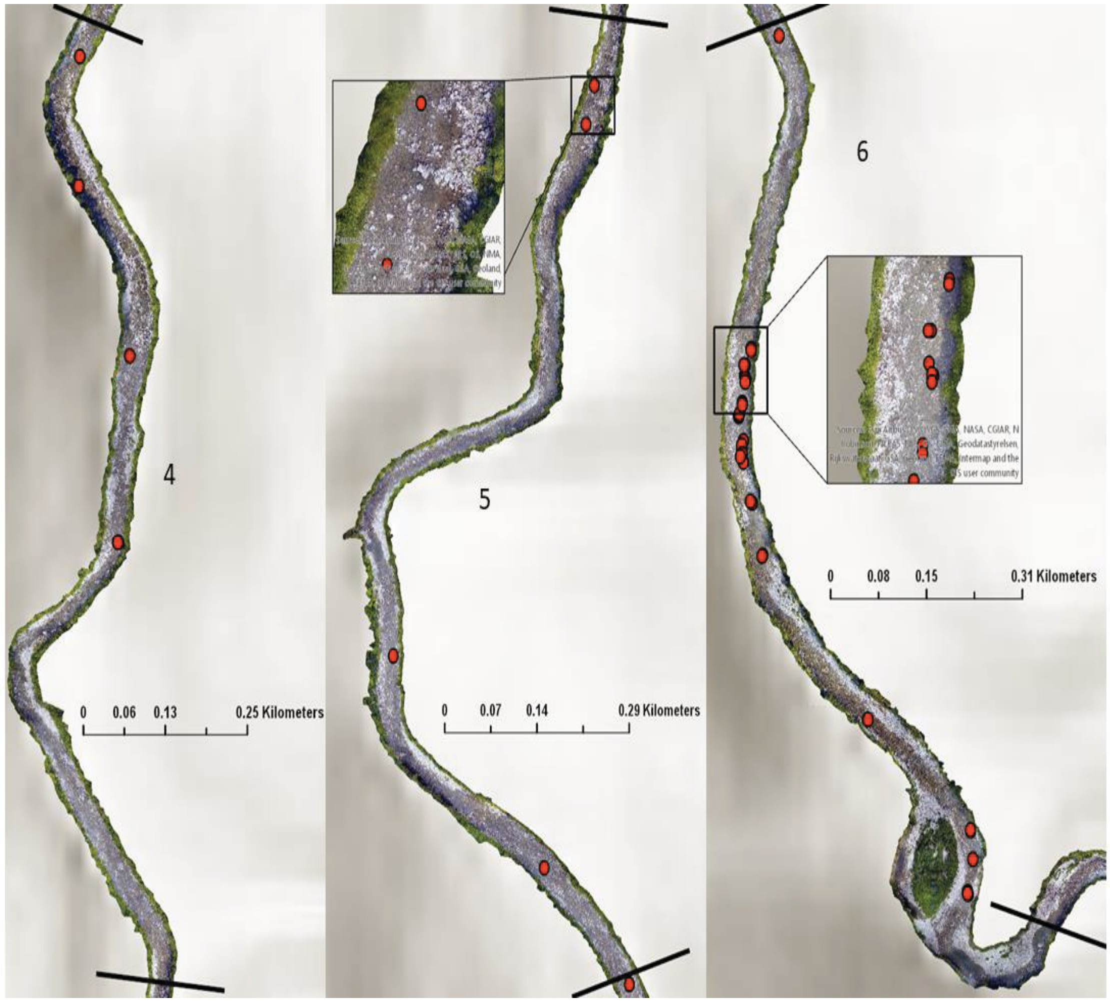

Figure 15: Corrected tracking data showing the GPS locations of the spawning salmon (red) within the Upper Salmon River for 2015-2017, for sections 4-6, mapped on orthomosaics. Black lines mark the division between sections. Insets show areas where clusters of spawning points were located

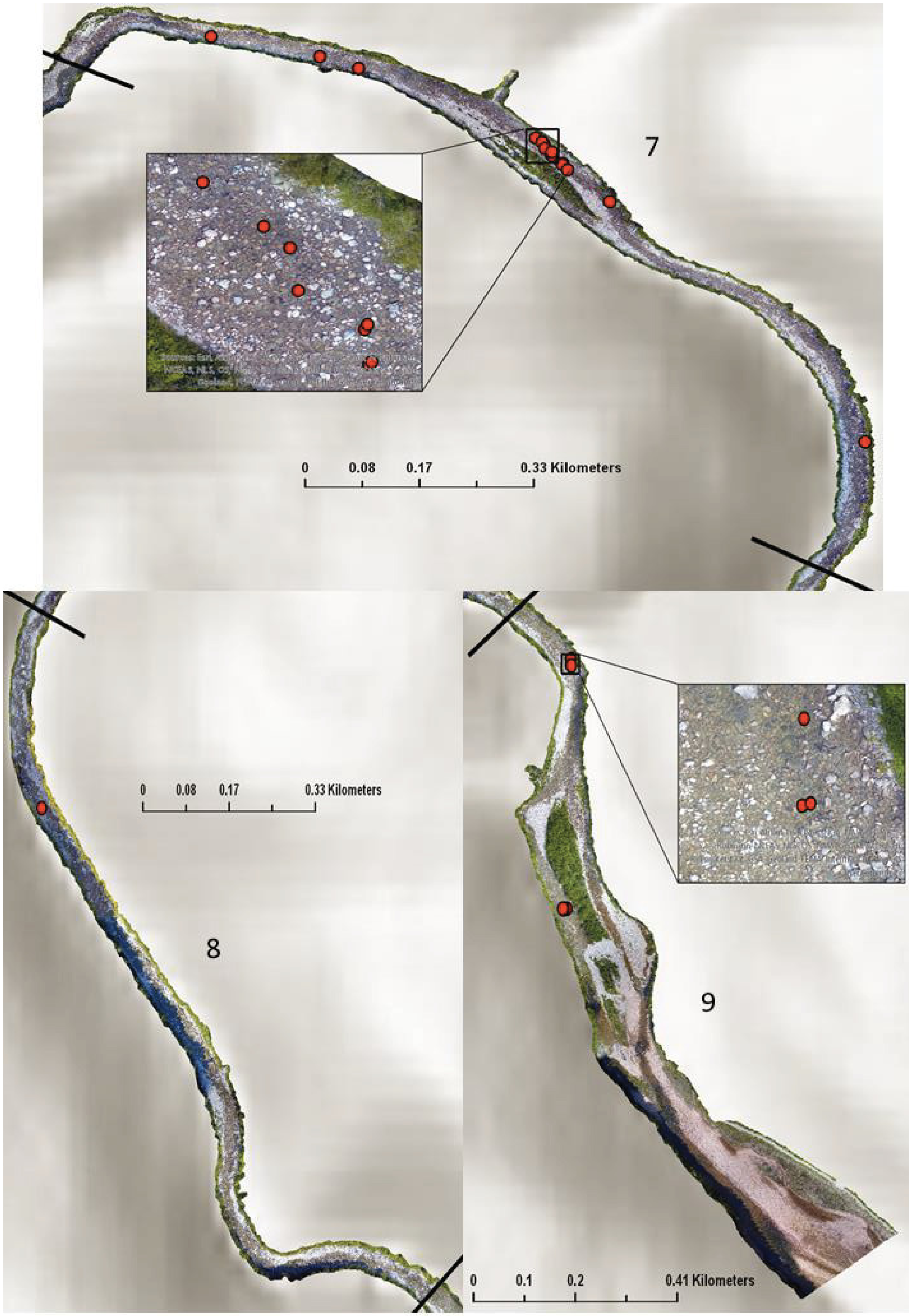

Figure 16: Corrected tracking data showing the GPS locations of the spawning salmon (red) within the Upper Salmon River for 2015-2017, for sections 7-9, mapped on orthomosaics. Black lines mark the division between sections. Insets show areas where clusters of spawning points were located.

3.3.2 Environmental Layers

The distinction between dry and wet areas of river substrate was important because substrate classification was conducted separately for each. However, for use in MaxEnt, substrate was merged between wet and dry since they overlap during other flood states of the river. Segmentation of the substrate into dry, submerged and vegetation was accomplished with an overall accuracy ranging from 79%-95% in the various river sections, with most values above 90% (Table 5). An overall accuracy of 89%, provides confidence for using these data in subsequent substrate classification. The northern upstream area of the river (sections 1-3) had the greatest relief and slope values, corresponding to large areas of riffles/pools, with the high elevation at the top of both waterfalls (Fig. 17). Macrohabitat types (pools, riffles, runs) are created by slope, flow and depth which also control scouring, gravel transport, and the distribution of substrate. Constriction of flow by boulders also influences the distribution of macrohabitat as well as wake regions behind the boulders leading to settlement of finer substrate. Image analysis indicated that northernmost river Section 1 comprised 61% of the substrate as boulders or larger, with 79% in Section 2, and 58% in Section 3 (Fig. 18).

In contrast, the southern end of the river (section 9) encompassing the mouth was the widest area, and had on average, lower elevation (Fig. 17). The river terminus is the base of the plateau, approaching sea level. There were channels that led to higher flow values, which can be seen to the right of an island within the river, with flow lowering as the river mouth widened (Fig. 19). The substrate within this section was dominated by finer material, with 77% either large gravel or smaller (Fig. 18).

Although clear patterns were present at either end of the river study area, where there were obvious geographical differences (waterfalls vs. the mouth of the river), the mid-section varied between riffles, runs and pools. The five middle sections (4-8) had large areas of both large gravel and large boulders (Fig. 18), and varying flow (Fig. 19) and slope (Fig. 17), with substrate and flow conditions indicative of suitable spawning habitat (Chapter 2). Object-based image analysis on substrate categorization of substrate (Table 6) had an accuracy of 79%-89%, with an overall accuracy of 83%.

In order to visualize river slope and flow as integrated measures, they were averaged for each section and graphed according to the linear distance covered by each section (Figs. 17, 19). Sections 1 and 2 had high areas of flow around the waterfalls that were averaged against the lows of the pools, causing an overall lower flow accumulation value. Flow accumulation peaked in sections 3 and 4, where the fork in the river converged, funneling water from both sections 1 and 2. From there, average flow accumulation steadily declined until sections 8 and 9, where the second peak occurred (Fig. 19). For section 8, the increase in flow may be attributed to flow constriction by an increase in large boulders this area had compared to sections 4-7 (Fig. 18). Section 9 had a higher percentage of smaller substrate (Fig. 18), but a large part of this section has islands and gravel bars, causing tighter channels that elevated the overall flow.

Table 5: Accuracy for the classification of dry, submerged and riverbank vegetation in each of the sections, where 1 is the most northern section and 9 is the most southern section.

Section	Accuracy
1	0.78
2	0.85
3	0.9
4	0.93
5	0.93
6	0.93
7	0.95
8	0.93
9	0.79

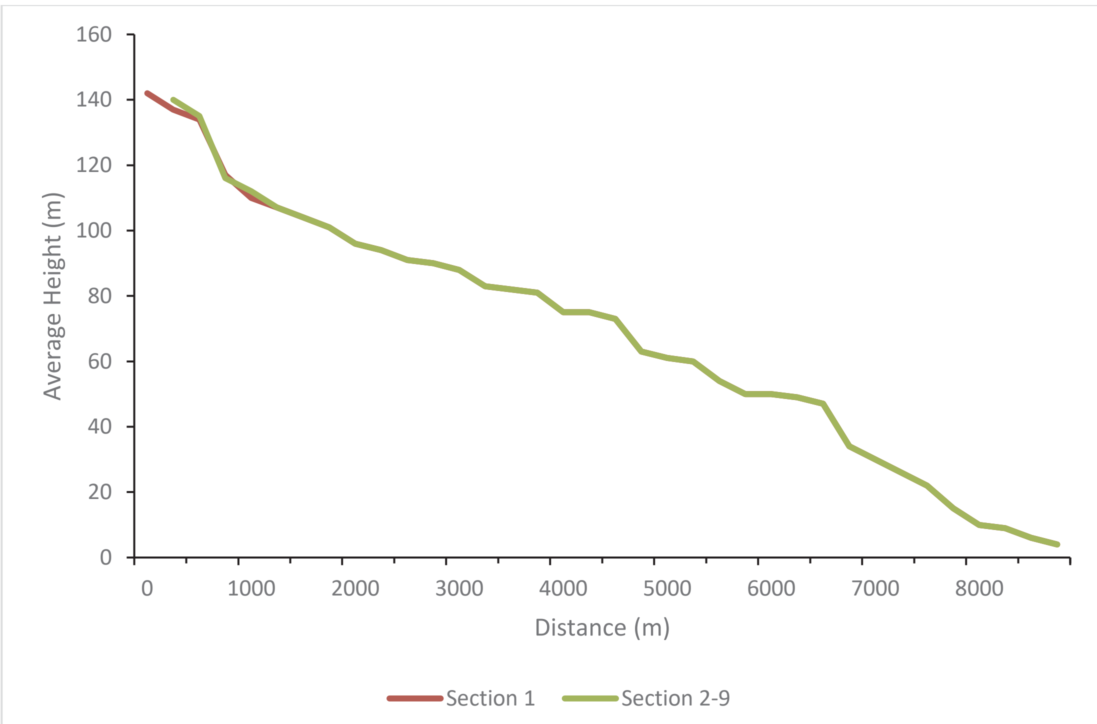

Figure 17: Average elevation values (meters) relative to the river graphed for each river section as broken up for Pix4D analysis, weighted by distance to show changes in slope between the upstream and downstream end of each section, with Section 1 & 2 being the furthest upstream and Section 9 being the mouth of the river. The orange line represents Section 1, graphed alongside Section 2, to show both extents of the forks meeting at Section 3 (~1500 m). 0 meter distance is the topmost point of Section 1 of the river, with Section 2 being 500 meters shorter and so starting at the 500 meter mark.

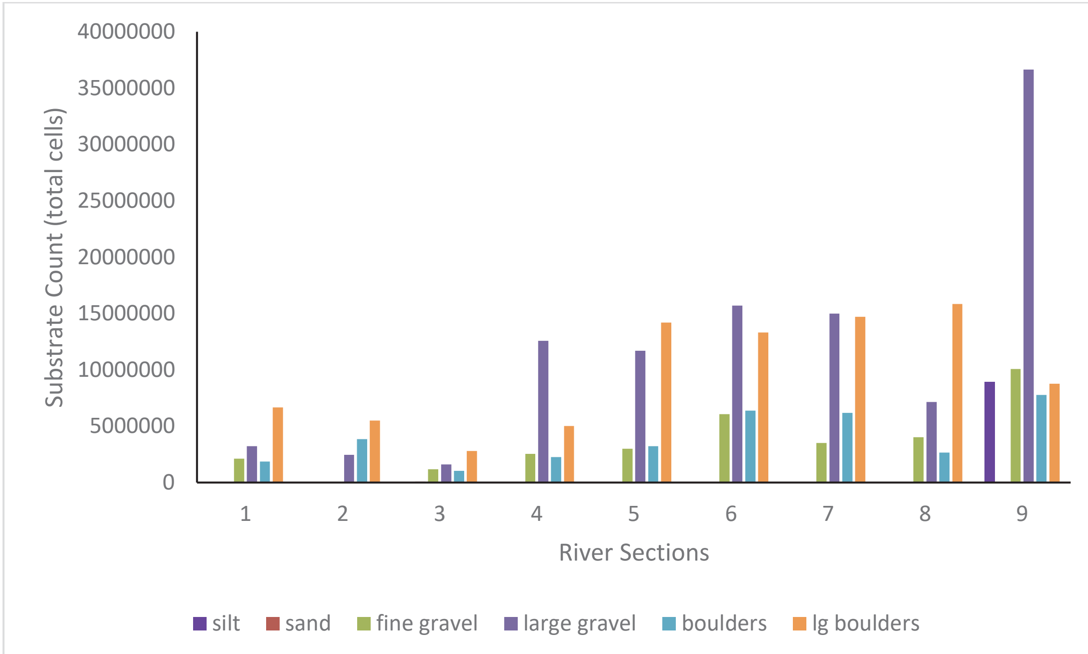

Figure 18: Object- based image analysis results of substrate size for the Upper Salmon River, divided into 9 sections as broken up for the Pix4D analysis, with Section 1 & 2 being the furthest upstream and Section 9 being the mouth of the river.

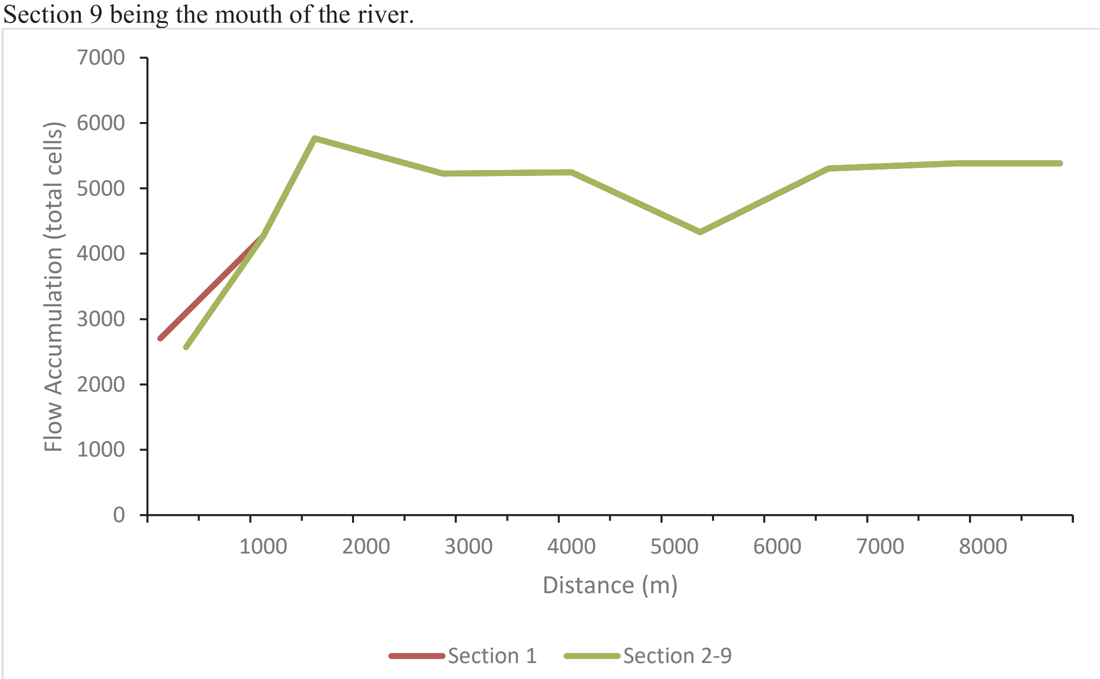

Figure 19: Average flow accumulation values graphed against the river sections as broken up for the Pix4D analysis, with each section shown as linear distance. Section 1 & 2 are the furthest upstream and Section 9 is the mouth of the river. The red line represents Section 1, graphed alongside Section 2, to show both extents of the forks meeting at Section 3 (~1500 m). 0 meter distance is the topmost point of Section 1 of the river, with Section 2 being 500 meters shorter and so starting at the 500 meter mark.

Table 6: Accuracy for the extraction of substrate in each of the river sections in the object-based image analysis, where 1 is the northernmost section and 9 is the southernmost section.

Section	Accuracy
1	0.81
2	0.82
3	0.79
4	0.8
5	0.89
6	0.81
7	0.84
8	0.86
9	0.86

3.3.3 MaxEnt

MaxEnt software produced a predictive distribution model of the Upper Salmon River based on the water flow, slope and substrate raster layers, along with fish presence data (Fig. 20-22). Warmer colors represent areas that had better predicted spawning habitat. In general, the model predicted that there was less suitable habitat within the northern end of the river, where flow was higher, and substrate was larger. Suitable habitat increased throughout the mid- and lower section of the river where substrate decreased in grain size. To better visualize the results, the predictive distributional model for each section was graphed as a histogram with 0 being a very low likelihood and 1 being a very high likelihood of spawning habitat (Fig. 23-24). Sections 1, 2 and 3 had the lowest mean values, with 0.27, 0.31 and 0.33. Sections 4 and 5 both had mean values of 0.41, with both models seeing peaks above 0.6. Section 6 had the highest mean of 0.44, followed by 7, 9 and 8 with means of 0.43, 0.43 and 0.37. The area under the curve (AUC) for the training data is 0.780 and 0.746 for the test data (Fig. 25), well above the 0.5 value that would result from a random prediction and considered to be acceptable (Mandrekar, 2010)

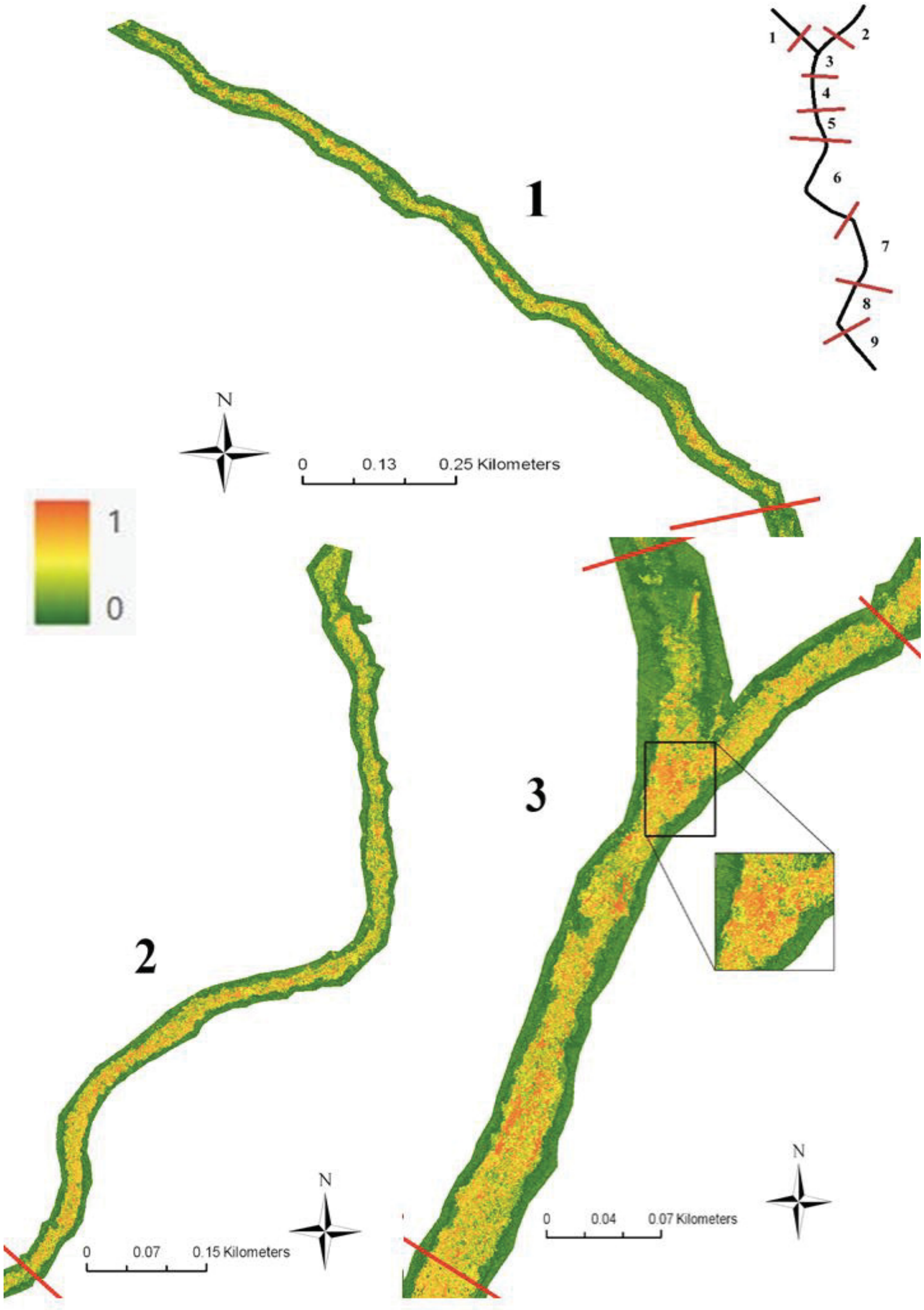

Figure 20: Predictive distributional model of salmon spawning grounds, red is a very high likelihood and green is a very low likelihood of spawning for sections 1-3. The arrangement of these sections along the river is indicated in the inset. A second inset shows a patch of high likelihood spawning grounds.

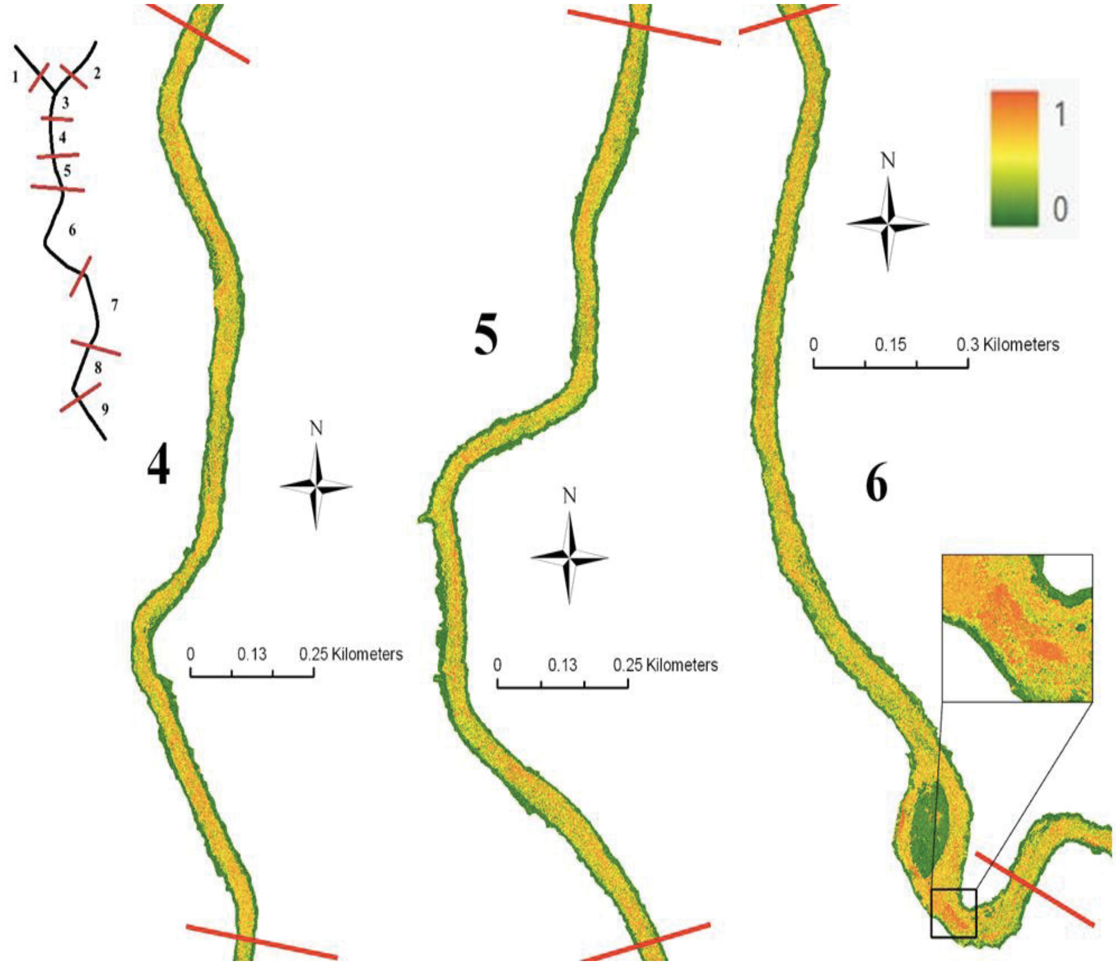

Figure 21: Predictive distributional model of salmon spawning grounds, red is a very high likelihood and green is a very low likelihood of spawning, for sections 4-6. The arrangement of these sections along the river is indicated in the inset. A second inset shows a patch of high likelihood spawning grounds.

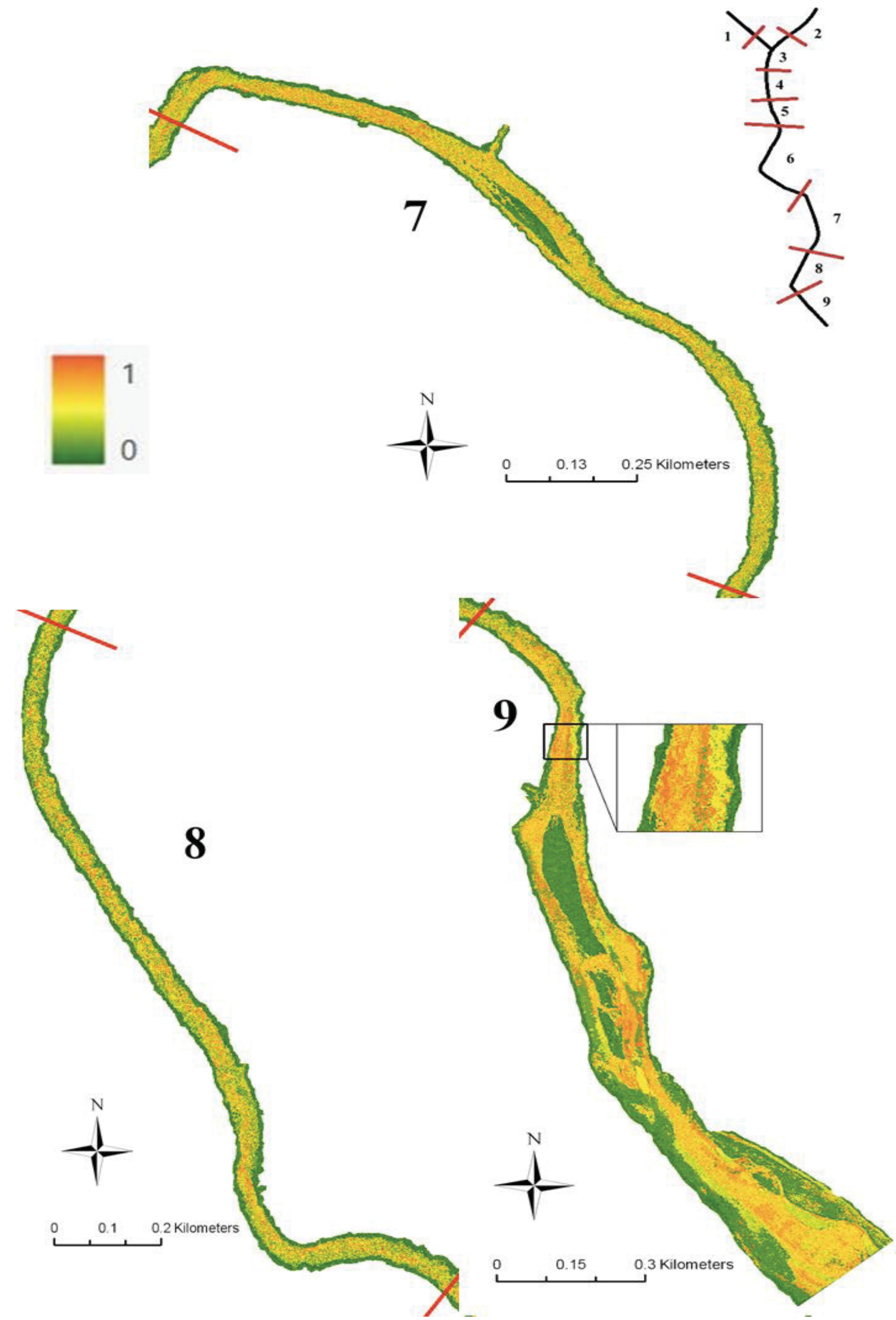

Figure 22: Predictive distributional model of salmon spawning grounds, red is a very high likelihood and green is a very low likelihood of spawning, for sections 7-9. The arrangement of these sections along the river is indicated in the inset. A second inset shows a patch of high likelihood spawning grounds.

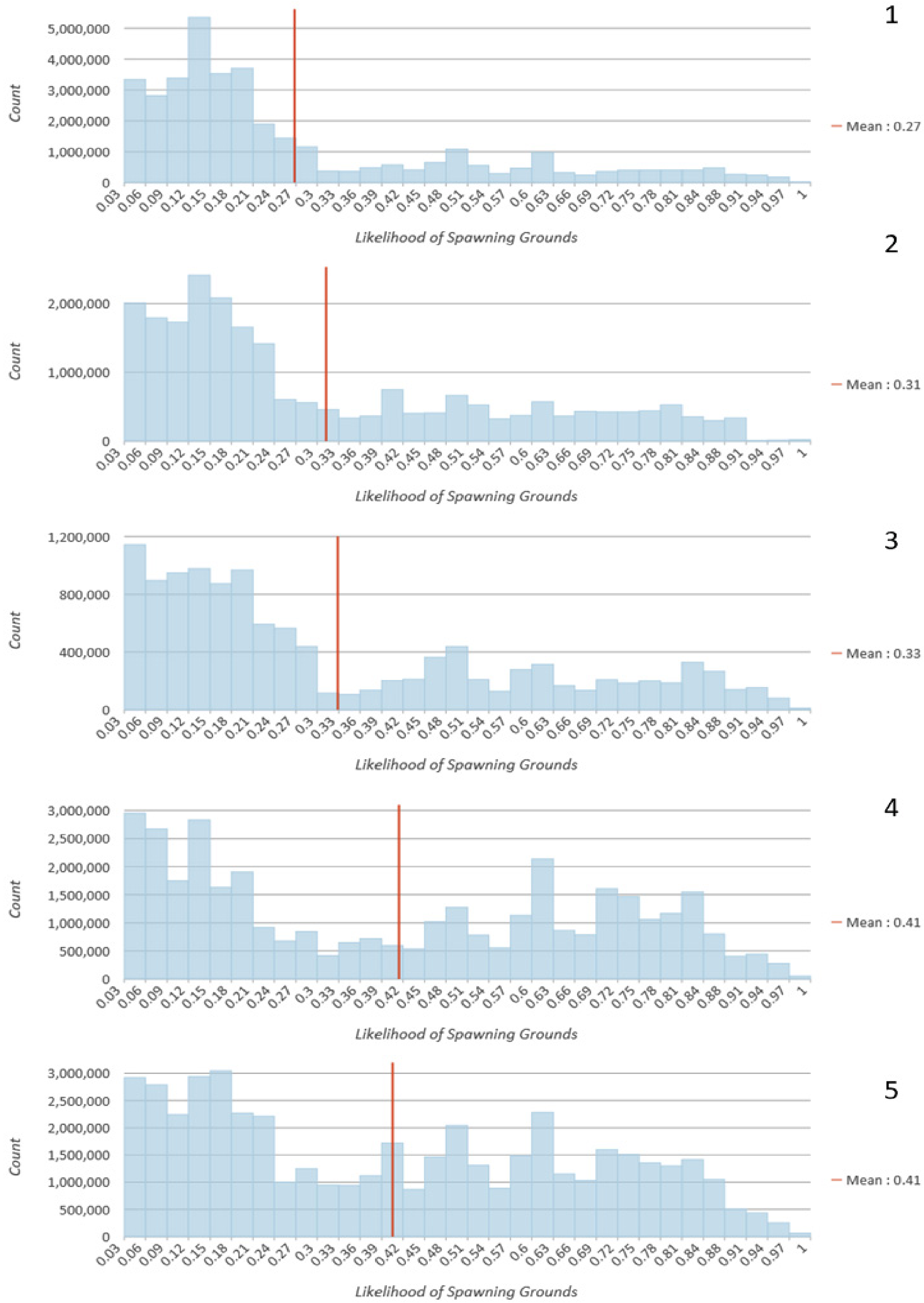

Figure 23: Maxent results of the predictive likelihood of Atlantic salmon spawning grounds for sections 1-5 of the USR. 0 is a low probability while 1 is a high probability. Mean is shown as a red line on the histogram.

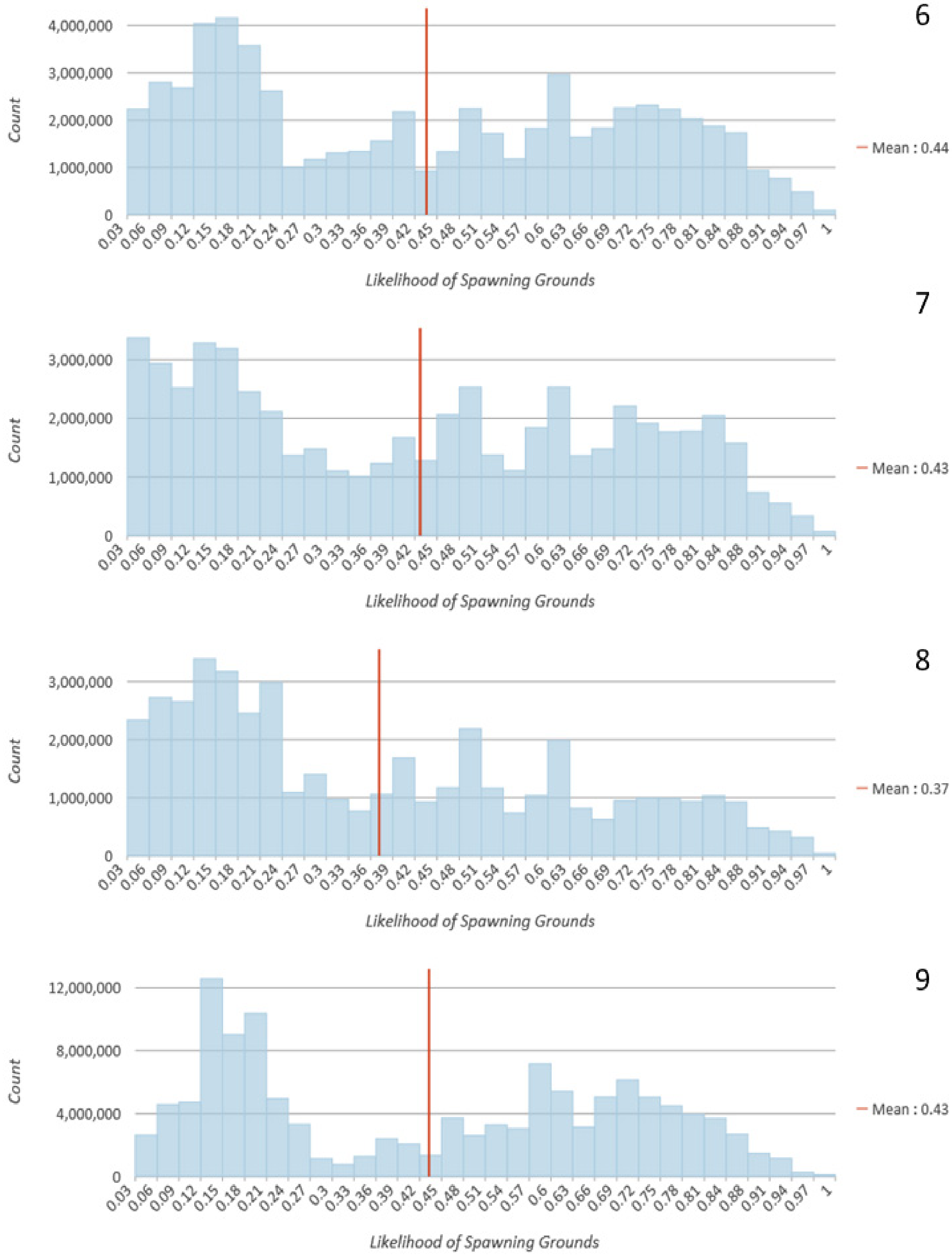

Figure 24: Maxent results of the predictive likelihood of Atlantic salmon spawning grounds for sections 6-9 of the USR. 0 is a low probability while 1 is a high probability. Mean is shown as a red line on the histogram.

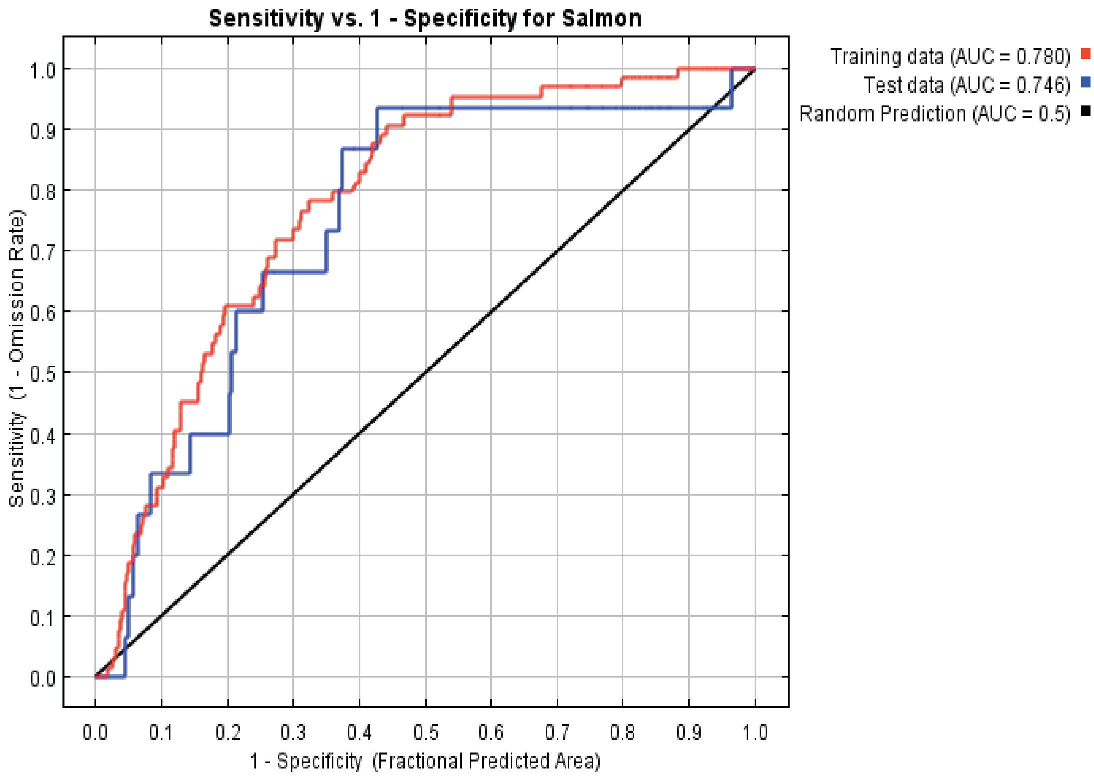

Figure 25: The receiver operating characteristic curves for the training and test data of the MaxEnt model.

Within the model, substrate had the highest contribution to prediction (Table 7) with 72.5%, followed by slope and flow accumulation. As correlated variables can skew the model contribution, permutation importance was also tested. Substrate had the highest permutation importance with 60.6% followed by slope and flow accumulation (Table 7). Response curves were graphed for each variables to better understand their affect on the model. Within the substrate, fine gravel had the highest response value, followed by boulders, and large gravel, with all other values showing a much lower response, and vegetation having a near zero response (Fig. 26A). Slope had a high response from 0 to 87 degrees, with a peak at 87 and a lull above 87 degrees (Fig. 26B). Model response to flow accumulation increased with flow accumulation, peaking at 35500 (Fig. 26C).

Table 7: The percent contribution and importance of the environmental raster layers (substrate, flow direction, flow accumulation and slope) for the MaxEnt model.

Variable	**Percent contribution**	**Permutation importance**
Substrate	72.5	60.6
Slope	19.5	29.5
Flow Accumulation	8	9.9

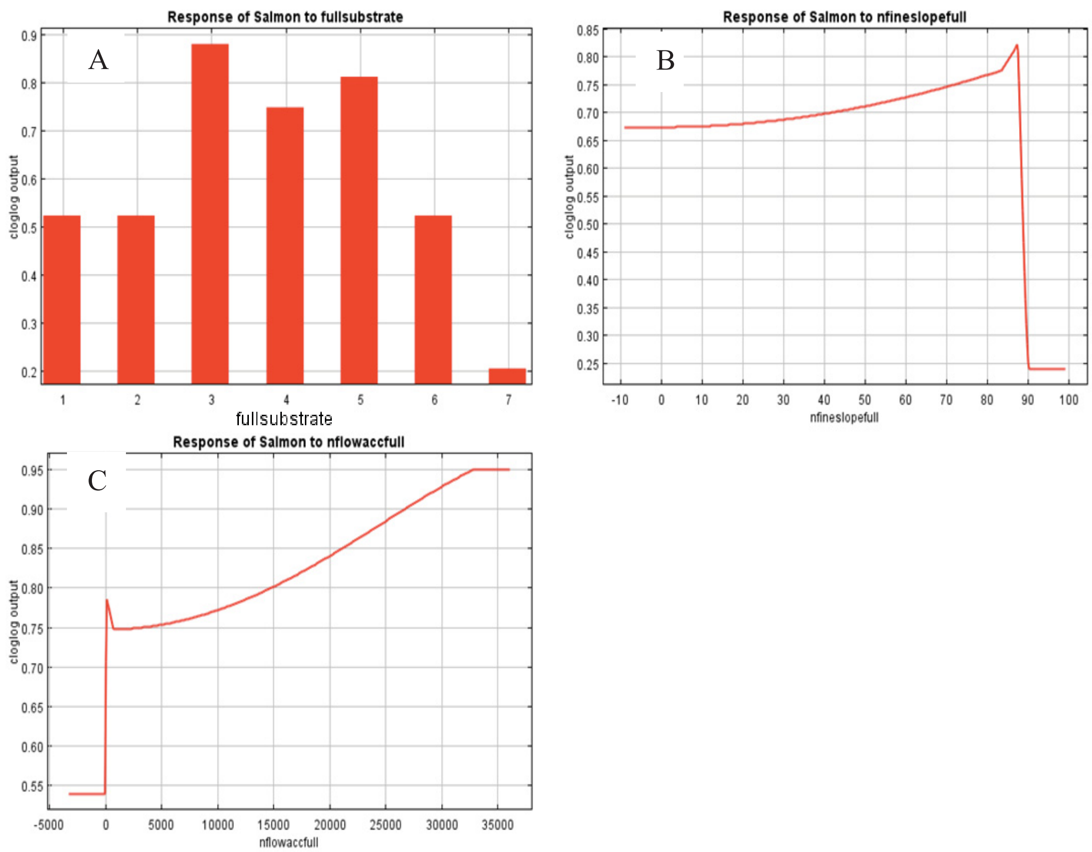

Figure 26: Response curves of the substrate (A), slope (B), and flow accumulation (C) raster layers in the MaxEnt model to the Atlantic salmon presence data for the full length of the river. Substrate 1-7 referring to silt (1), sand (2), fine gravel (3), large gravel (4), block (5), large boulders (6) and vegetation (7).

3.4 DISCUSSION

This study sought to test the ability to create a species distribution model for Atlantic salmon using environmental layers from DEM's created using imagery captured by UAV's. Chapter 2 results demonstrated that water depth and riffles did not greatly affect the accuracy of the raster layer, so that application of object-based image analysis was applicable to the entire orthomosaic. With the high resolution of the DEM, the accuracy of substrate classification (0.83), and the corrected georeferenced presence data, the model was considered to be a reasonable approach. Mapped spawning locations of Atlantic salmon with environmental data along an entire river section are not common as they require extensive groundtruthing, and so many models rely on fine scale sampling at spawning sites.

3.4.1 MaxEnt

When environmental variables are correlated in MaxEnt models, the response curves can be skewed as the variables are not independent (Philips et al., 2017). In this case, all variables were correlated as substrate settles based on water flow and slope is a determinant factor of said water flow. To counter this problem, permutation importance examines how randomly altering variables within the training points will affect the AUC, and their importance in the model. Although slope and flow both had impacts on the model, and thresholds for salmon spawning, substrate had the largest percent contribution and permutation contribution, making up over 60% in both cases. Overall, the model predicted substantial amounts of the middle and lower sections of the river to be potential spawning habitat, with little to no potential spawning habitat in the northern (upper) area of the river. This trend was caused by the highest contributing factor, substrate. Generally, larger substrate was located more extensively upstream, while smaller substrate was relatively more important downstream. The settlement of sediment is due to fluvial sorting, causing smaller sediment to accumulate downstream (Rice, 1998; Davey & Lapointe, 2006).

Although other factors such as flow play a role in habitat selection, spawning is strongly dependent on sediment (Heggenes, 1990; Armstrong et al., 2003; Louhi, 2008; Davey & Lapointe, 2007). Small substrate decreases aeration within the stream bed which lowers the survivability of eggs (Lapointe et al., 2004; Louhi, 2008). If substrate is too large salmon will be unable to move the sediment to dig redds. Salmon will select and successfully spawn in areas of reduced flow where substrate is adequate (Barlaup et al., 2008).

3.4.1.1 Substrate

Substrate is not only important for spawning, but at all life stages and has been directly linked to carrying capacities of rivers (Fjellheim, et al., 2003). As Atlantic salmon spend a considerable portion of their lives as parr in the river, increasing habitat suitability for both spawning and juveniles is important. Substrate manipulation has been shown to be the most effective habitat restoration technique, with the addition of boulder clusters greatly increasing the density of juveniles (Van Zyll De Jong et al, 1997). The declining state of Atlantic salmon populations has led to a surge in habitat restoration, as well as repopulation programs (Clarke et al., 2016; Department of Fisheries and Oceans Canada, 2010; Hvidsten & Johnsen, 1992). Rivers are complex habitats made up of many interdependent features (Schumm, 2007), but species distribution models may help to identify which variables are most important as targets of habitat restoration. Running the model with presence data for juvenile salmon would be a valuable application of the approach since the environmental rasters are already established.

In this study, ideal spawning substrate was considered to be fine gravel (2mm-5cm) based on Armstrong et al (2003) and Louhi (2008), but it should be noted that salmon can spawn within the smaller grainsize range of the large gravel (5cm-20cm) up to 12.5 cm. Salmon eggs require high concentrations of oxygen (Louhi, 2008) and salmon prefer to spawn in well aerated fine gravel compared to substrates of smaller grainsize such as sand. The presence of fine-grained sediment can also obstruct the emergence of fry from the redds (Kondolf, 2000; Lapointe et al., 2005). The nests are dug in the gravel to allow for the protection against predation, gravel shifts, freezing and low water conditions (Fleming, 1998). Unexpectedly, boulders and large gravel which could not be moved by fish also had high habitat suitability in the SDM. This is most likely because substrate deposit patterns are related to water flow, which is variable (Kodama, 1994). Areas where water flow may have allowed for substrates of larger grainsize to deposit (e.g. due to a rainfall even) may lessen, allowing for substrate of smaller grainsize to be deposited in the same area. Moreover, coarser substrate depositing can also lessen the flow on an area, allowing for fine substrates to be deposited downstream of it. This is seen in core samples obtained at spawning sites which showed substrate the size of boulders compromising 40% of the cores (Peterson, 1978; Gibson, 1993). This interdependence between flow and substrate would cause the model to recognize both the boulders and large gravel where the salmon are spawning even though they are not utilized as spawning substrate. Less frequently salmon will spawn in larger substrate, especially in larger rivers where they will also spawn in deeper water (Louhi, 2008). Other classes, both larger and smaller than the fine gravel – boulders and sand, were relatively less important in the model, matching the substrate preferences seen in other studies (Armstrong et al., 2003). Although substrate size categories were based off Borsányi et al., (2004) other studies use different size categories (Kondolf, 2000; Gibson, 1993). Even compilation studies exploring substrate size preferences do not allow consistent comparisons (Armstrong et al., 2003; Louhi, 2008).

Although the model included measurements of flow, slope and substrate, spawning habitat is also dependent on water depth (Armstrong et al., 2003) which was not included. With the variability of water levels in the river, and the fact that all measurements were obtained during low water levels, there was no way to calculate water depth from the DEM without more information such as an average water depth for the duration of the spawning season. The salmon spawning dates varied from the start of November till the end of December, in which time the water level is likely to vary due to rain or snow events.

3.4.2 Limitations, Advancements & Future Direction

Often, limiting factors in broad-scale analysis include computing power and processing time. In this case, the model was limited by the number of runs it was able to process, with a single MaxEnt run taking upwards of 8 hours to complete. This limited the testing of multiple layers through the model e.g. different slope resolutions & additional layers. Model accuracy could be further improved through this testing.

Furthermore, as resolution was fine-scaled, slope values for the model were also fine-scaled. Additional testing of slope layer resolutions may allow for further insight into salmon spawning habitat.

Although there are studies that seek to characterize spawning habitat, models of this scale using similar technology are relatively new, with studies only beginning to explore the uses of RGB (Red Green Blue) images from UAV's for substrate analysis (Arif et al., 2017; Danhoff & Huckins, 2020). These models have wide applicability to determine which rivers have spawning potential for river restoration and restocking of Atlantic salmon. Similar models can be constructed in River 2D, which uses a hydrodynamic model to evaluate fish habitat, but these require extensive groundtruthing in the form of sampling (Gard, 2006). Although groundtruthing can provide the model with additional data such as water depth which was not included in my DEM analysis, substrate is extrapolated from point data. As substrate is arguably the most important feature in spawning habitat a UAV substrate analysis, which requires less sampling and provides more coverage, is more efficient for preliminary analysis of spawning habitat.

Mapping the river by UAV substrate analysis is also beneficial to projects that seek to alter bed composition to enhance habitat, e.g. spawning substrate (Fjellheim et al., 2003). This type of model could also be applied to different life stages such as juvenile habitat. In the present work, substrate had the largest influence on prediction of spawning habitat. Further refinement such as changing the raster layers to test different substrate size categories may increase the response of ideal substrate and lead to a more standardized system. SDM are often limited by environmental layers

(Srivastava, Lafond & Griess, 2019), but UAV's provide capacity to quantify habitat and more fully exploit this approach to identify spawning grounds, holding/feeding areas, and restoration potential in salmonid rivers (Roncoroni & Lane, 2019).

3.5 CONCLUSSION

This study has shown that UAV can be used to successfully extract environmental layers from rivers. Using both the UAV derived orthomosaics and DEM, raster layers containing substrate size, slope and flow were codded. With the addition of presence data, an SDM was modelled successfully. The results of this model added evidence towards the importance of substrate to Atlantic salmon for spawning, as it was seen to have the largest impact on the model results. In conclusion, UAV are a practical high-resolution tool in habitat analysis of rivers for spawning salmon. Further study should look at implementing similar methods to juvenile habitat and other rivers.

CHAPTER 4 CONCLUSSION

Current methods for habitat analysis of Atlantic salmon are expensive, time consuming and conducted at localized scales. Habitat mapping using the latest aerial remote sensing tools (UAVs) provides advantages to understanding salmon habitat preferences through improved understanding of the structural complexities of rivers. Understanding the structural complexity of rivers is vital to restoration projects that seek to increase the population of endangered species, such as IBoF salmon. With the potential that SDM have in analyzing spawning habitat, a practical way to extract environmental data from rivers was needed. With substrate being a vital component in the structural complexity, an accurate method for substrate grainsize analysis was also needed. This thesis explored the feasibility, limitations and accuracy of using a UAV to extract environmental data from river habitats.

Chapter 2 observed the accuracy of orthomosaics in the varying physical properties of the river found in macrohabitats. As pools, riffles and runs are ways to classify habitat by similar slope, flow and substrate, these were used to denote transects. The results showed that despite varying physical conditions found in the transects (e.g. Depth and clarity) accuracy was consistently high, with only riffles causing a decrease in accuracy. This chapter also compared the transects to groundtruthing data to determine if substrate size was skewed by water. No magnification effect was found to be apparent at the depths tested. Although the UAV could not measure all the variables available that groundtruthing can, it was far more efficient in the field and allowed for a larger section of the river to be surveyed with a high accuracy in a shorter timespan.

Chapter 3 demonstrated how a UAV can be used to create environmental layers through analysis of both the orthomosaics and DEMs for the creation of an SDM. Building on the methods tested in Chapter 1, a substrate analysis was conducted for ~10 km of river on an orthomosaic. Along with this, slope and flow were determined from the DEM and incorporated as raster layers. This environmental information and presence data from spawning salmon were input into MaxEnt to model potential spawning habitat. The model was determined to be sound, and the results indicated that substrate size was a large determining factor in Atlantic salmon spawning habitat. With the success of the model on spawning habitat, further analysis should be conducted to expand to juvenile habitat.

As a whole, this thesis demonstrates that using a UAV to analysis river habitat is a viable option. Environmental data from the substrate, flow and slope can all be determined using a UAV with a relatively high accuracy despite varying physical conditions of a river. The methods, and techniques derived through this thesis, should be considered for future use in analyzing potential salmon spawning grounds, as well as expanded for juvenile habitat.

REFERENCES

Allan, J. D., & Castillo, M. M. (2007). *Stream ecology: structure and function of running waters*. Springer Science & Business Media.

Amiro, P. G., Brazner, J. C., & Giorno, J. L. (2009). *Assessment of the recovery potential for the Atlantic salmon designatable unit Inner Bay of Fundy: threats*. Fisheries and Oceans Canada, Science.

Arif, M. S. M., Gülch, E., Tuhtan, J. A., Thumser, P., & Haas, C. (2017). An investigation of image processing techniques for substrate classification based on dominant grain size using RGB images from UAV. *International Journal of Remote Sensing*, 38(8-10), 2639-2661.

Armstrong, J. D., Kemp, P. S., Kennedy, C. J., Ladle, M., & Milner, N. J. (2003). Habitat requirements of Atlantic salmon and brown trout in rivers and streams. *Fisheries Research*, *62*, 143–170.

Baglinière, J. L., & Champigneulle, A. (1986). Population estimates of juvenile Atlantic salmon, *Salmo salar*, as indices of smolt production in the R. Scorff, Brittany. *Journal of Fish Biology*, *29*(4), 467-482.

Barlaup, B. T., Gabrielsen, S. E., Skoglund, H., & Wiers, T. (2008). Addition of spawning gravel—a means to restore spawning habitat of Atlantic salmon (*Salmo salar L.*), and Anadromous and resident brown trout (*Salmo trutta L.*) in regulated rivers. *River Research and Applications*, *24*(5), 543-550.

Borsányi, P., Alfredsen, K., Harby, A., Ugedal, O., & Kraxner, C. (2004). A meso-scale habitat classification method for production modelling of Atlantic salmon in Norway. *Hydroécologie Appliquée*, *14*, 119-138.

Brockmark, S., Neregård, L., Bohlin, T., Björnsson, B. T., & Johnsson, J. I. (2007). Effects of rearing density and structural complexity on the pre-and postrelease performance of Atlantic salmon. *Transactions of the American Fisheries Society*, *136*(5), 1453-1462.

Brown, C., & Laland, K. (2001). Social learning and life skills training for hatchery reared fish. *Journal of Fish Biology*, *59*(3), 471-493.

Buisson, L., Blanc, L., & Grenouillet, G. (2008). Modelling stream fish species distribution in a river network: the relative effects of temperature versus physical factors. *Ecology of Freshwater Fish*, 17(2), 244-257.

Burns, J. H. R., & Delparte, D. (2017). Comparison of commercial structure-from-motion photogrammetry software used for underwater three-dimensional modeling of coral reef environments. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*, 127.

Chesley, J. T., Leier, A. L., White, S., & Torres, R. (2017). Using unmanned aerial vehicles and structure-from-motion photogrammetry to characterize sedimentary outcrops: An example from the Morrison Formation, Utah, USA. *Sedimentary Geology*, *354*, 1-8.

Clarke, C. N., Fraser, D. J., & Purchase, C. F. (2016). Lifelong and carry-over effects of early captive exposure in a recovery program for Atlantic salmon (*Salmo salar*). *Animal Conservation*, *19*(4), 350-359.

COSEWIC. (2006). COSEWIC Assessment and Update Status Report on the Atlantic Salmon *Salmo salar* (Inner Bay of Fundy Populations) in Canada.

Coulombe-Pontbriand, M., & Lapointe, M. (2004). Geomorphic controls, riffle substrate quality, and spawning site selection in two semi-alluvial salmon rivers in the Gaspé Peninsula, Canada. *River Research and Applications*, *20*(5), 577-590.

Cunjak, RA (1988). Behavior and microhabitat of young Atlantic salmon (*Salmo salar*) during winter. *Canadian Journal of Fisheries and Aquatic Sciences*, *45* (12), 2156-2160.

Cunliffe, A. M., Brazier, R. E., & Anderson, K. (2016). Ultra-fine grain landscape-scale quantification of dryland vegetation structure with drone-acquired structure-from-motion photogrammetry. *Remote Sensing of Environment*, *183*, 129-143.

Dadswell, M. J. (1968). *Atlantic Salmon (Salmo Salar) Investigations in the Point Wolfe and Upper Salmon Rivers, Fundy National Park*. Canadian Wildlife Service.

Dadswell, M. J., Spares, A. D., Reader, J. M., & Stokesbury, M. J. W. (2010). The North Atlantic subpolar gyre and the marine migration of Atlantic salmon Salmo salar: The 'Merry-Go-Round' hypothesis. *Journal of Fish Biology*, *77*(3), 435-467.

Danhoff, B. M., & Huckins, C. J. (2020). Modelling submerged fluvial substrates with structure-from-motion photogrammetry. *River Research and Applications*, 36(1), 128-137.

Davey, C., & Lapointe, M. (2007). Sedimentary links and the spatial organization of Atlantic salmon (*Salmo salar*) spawning habitat in a Canadian Shield river. *Geomorphology*, *83*(1-2), 82-96.

Department of Fisheries and Oceans Canada. 2010. Recovery Strategy for the Atlantic salmon (*Salmo salar*), inner Bay of Fundy populations [Final]. In *Species at Risk Act Recovery Strategy Series.* Fisheries and Oceans Canada, Ottawa, Ontario.

Dubuc, L. J., Krohn, W. B., & Owen Jr, R. B. (1990). Predicting occurrence of river otters by habitat on Mount Desert Island, Maine. *The Journal of Wildlife Management*, 594-599.

Elith, J., & Leathwick, J. R. (2009). Species distribution models: ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics*, *40*, 677-697.

Einum, S., Nislow, K. H., Reynolds, J. D., & Sutherland, W. J. (2008). Predicting population responses to restoration of breeding habitat in Atlantic salmon. *Journal of Applied Ecology*, *45*(3), 930-938.

Emerson, P. W. (2014). *In-stream habitat enhancement for juvenile Atlantic salmon in the Little Main Restigouche River, New Brunswick* (Doctoral dissertation, University of New Brunswick).

Everest FH, Beschta RL, Scrivener JC, Koski KV, Sedell JR, Cederholm CJ. 1987. Fine sediment and salmonid production: a paradox. In *Streamside Management and Forestry and Fishery Interactions*, Salo EO, Cundy TW (eds). College of Forest Resources, University of Washington; 89–142.

Finstad, A. G., Einum, S., Forseth, T., & Ugedal, O. (2007). Shelter availability affects behaviour, size-dependent and mean growth of juvenile Atlantic salmon. *Freshwater Biology*, *52*(9), 1710-1718.

Fitzsimons, J. D., Dalton, A., MacVeigh, B., Heaton, M., Wilson, C., & Honeyfield, D. C. (2013). Use of stable isotopes to identify redds of putative hatchery and wild Atlantic Salmon and evaluate their spawning habitat and egg thiamine status in a Lake Ontario tributary. *North American Journal of Fisheries Management*, *33*(4), 741-753.

Fjellheim, A., Barlaup, B. T., Gabrielsen, S. E., & Raddum, G. G. (2003). Restoring fish habitat as an alternative to stocking in a river with strongly reduced flow. *International Journal of Ecohydrology & Hydrobiology*, *3*(1), 17-26.

Fleming, I. A. (1998). Pattern and variability in the breeding system of Atlantic salmon (*Salmo salar*), with comparisons to other salmonids. *Canadian Journal of Fisheries and Aquatic Sciences*, *55*(S1), 59-76.

Gard, M. (2006). Modeling changes in salmon spawning and rearing habitat associated with river channel restoration. *International Journal of River Basin Management*, *4*(3), 201-211.

Garman, G. C., & Moring, J. R. (1991). Initial effects of deforestation on physical characteristics of a boreal river. *Hydrobiologia*, *209*(1), 29-37.

Gibson, R. J. (1993). The Atlantic salmon in fresh water: spawning, rearing and production. *Reviews in Fish Biology and Fisheries*, *3*(1), 39–73. https://doi.org/10.1007/BF00043297

Gorman, O. T., & Karr, J. R. (1978). Habitat structure and stream fish communities. *Ecology*, *59*(3), 507-515.

Hamilton, S. K. (2002). Human impacts on hydrology in the Pantanal wetland of South America. *Water Science and Technology*, *45*(11), 35-44.

Hansen, L. P., & Quinn, T. P. (1998). The marine phase of the Atlantic salmon (Salmo salar) life cycle, with comparisons to Pacific salmon. *Canadian Journal of Fisheries and Aquatic Sciences*, *55*(S1), 104-118.

Harte, J., & Newman, E. A. (2014). Maximum information entropy: a foundation for ecological theory. *Trends in Ecology & Evolution*, *29*(7), 384-389.

Heggenes, J. (1990). Habitat utilization and preferences in juvenile Atlantic salmon (*Salmo salar*) in streams. *Regulated Rivers: Research & Management*, *5*(4), 341-354.

Heggenes, J., & Saltveit, S. J. (1990). Seasonal and spatial microhabitat selection and segregation in young Atlantic salmon, *Salmo salar L*., and brown trout, *Salmo trutta L*., in a Norwegian river. *Journal of Fish Biology*, *36*(5), 707-720.

Hilton, J., O'Hare, M., Bowes, M. J., & Jones, J. I. (2006). How green is my river? A new paradigm of eutrophication in rivers. *Science of the Total Environment*, *365*(1-3), 66-83.

Höjesjö, J., Kaspersson, R., & Armstrong, J. D. (2016). Size-related habitat use in juvenile Atlantic salmon: the importance of intercohort competition. *Canadian Journal of Fisheries and Aquatic Sciences*, *73*(8), 1182-1189.

Holbrook SJ, Schmitt RJ. (2002). Competition for shelter space causes density-dependent predation mortality in damselfishes. *Ecology* 83:2855–2868

Horton, A. J., Constantine, J. A., Hales, T. C., Goossens, B., Bruford, M. W., & Lazarus, E. D. (2017). Modification of river meandering by tropical deforestation. *Geology*, *45*(6), 511-514.

Hossain, M. D., & Chen, D. (2019). Segmentation for Object-Based Image Analysis (OBIA): A review of algorithms and challenges from remote sensing perspective. *ISPRS Journal of Photogrammetry and Remote Sensing*, *150*, 115-134.

Hvidsten, N. A., & Johnsen, B. O. (1992). River bed construction: impact and habitat restoration for juvenile Atlantic salmon, *Salmo salar L*., and brown trout, *Salmo trutta L*. *Aquaculture Research*, *23*(4), 489-498.

Irvine, J. R., Gross, M. R., Wood, C. C., Holtby, L. B., Schubert, N. D., & Amiro, P. G. (2005). Canada's Species at Risk Act: An opportunity to protect endangered salmon. *Fisheries*, *30*(12), 11-19.

Johnson, C. J., & Gillingham, M. P. (2005). An evaluation of mapped species distribution models used for conservation planning. *Environmental Conservation*, 117-128.

Jonsson, N., Hansen, L. P., & Jonsson, B. (1991). Variation in age, size and repeat spawning of adult Atlantic salmon in relation to river discharge. *The Journal of Animal Ecology*, 937-947.

Jonsson, B., & Jonsson, N. (2003). Migratory Atlantic salmon as vectors for the transfer of energy and nutrients between freshwater and marine environments. *Freshwater Biology*, *48*(1), 21-27.

Jowett, I. G. (1993). A method for objectively identifying pool, run, and riffle habitats from physical measurements. *New Zealand Journal of Marine and Freshwater Research*, *27*(2), 241-248.

Kodama, Y. (1994). Downstream changes in the lithology and grain size of fluvial gravels, the Watarase River, Japan; evidence of the role of abrasion in downstream fining. *Journal of Sedimentary Research*, *64*(1a), 68-75.

Kondolf, G. M. (2000). Assessing salmonid spawning gravel quality. *Transactions of the American Fisheries Society*, *129*(1), 262-281.

Lane, S. N. (2000). The measurement of river channel morphology using digital photogrammetry. *The Photogrammetric Record*, *16*(96), 937-961.

Lapointe, MF, Bergeron, NE, Bérubé, F., Pouliot, MA, & Johnston, P. (2004). Interactive effects of substrate sand and silt contents, redd-scale hydraulic gradients, and interstitial velocities on egg-to-emergence survival of Atlantic salmon (*Salmo salar*). *Canadian Journal of Fisheries and Aquatic Sciences*, *61* (12), 2271-2277.

Lawler, J. J., Wiersma, Y. F., & Huettmann, F. (2011). Using species distribution models for conservation planning and ecological forecasting. In *Predictive species and habitat modeling in landscape ecology* (pp. 271-290). Springer, New York, NY.

Limburg, K. E., & Waldman, J. R. (2009). Dramatic declines in North Atlantic diadromous fishes. *BioScience*, *59*(11), 955-965.

Linnansaari, T., Alfredsen, K., Stickler, M., Arnekleiv, J. V., Harby, A., & Cunjak, R. A. (2009). Does ice matter? Site fidelity and movements by Atlantic salmon (*Salmo salar L.*) parr during winter in a substrate enhanced river reach. *River Research and Applications*, *25*(6), 773-787.

Louhi, P., Mäki-Petäys, A., & Erkinaro, J. (2008). Spawning habitat of Atlantic salmon and brown trout: general criteria and intragravel factors. *River Research and Applications*, *24*(3), 330-339.

Maki-Petäys, A., Muotka, T., Huusko, A., Tikkanen, P., & Kreivi, P. (1997). Seasonal changes in habitat use and preference by juvenile brown trout, *Salmo trutta*, in a northern boreal river. *Canadian Journal of Fisheries and Aquatic Sciences*, *54*(3), 520-530.

Malcolm, I. A., Soulsby, C., Youngson, A. F., Hannah, D. M., McLaren, I. S., & Thorne, A. (2004). Hydrological influences on hyporheic water quality: implications for salmon egg survival. *Hydrological Processes*, *18*(9), 1543-1560.

Mandrekar, J. N. (2010). Receiver operating characteristic curve in diagnostic test assessment. *Journal of Thoracic Oncology, 5*(9), 1315-1316.

McCoy, E. D., & Bell, S. S. (1991). Habitat structure: the evolution and diversification of a complex topic. In *Habitat structure* (pp. 3-27). Springer, Dordrecht.

Mills, D. (1989). *Ecology and management of Atlantic salmon*. Springer Science & Business Media.

Mitchell, J., McKinley, R. S., Power, G., & Scruton, D. A. (1998). Evaluation of Atlantic salmon parr responses to habitat improvement structures in an experimental channel in Newfoundland, Canada. *Regulated Rivers: Research & Management: An International Journal Devoted to River Research and Management*, 14(1), 25-39.

Moir, H. J., Gibbins, C. N., Buffington, J. M., Webb, J. H., Soulsby, C., & Brewer, M. J. (2009). A new method to identify the fluvial regimes used by spawning salmonids. *Canadian Journal of Fisheries and Aquatic Sciences*, *66*(9), 1404-1408.

Montgomery, DR, Beamer, EM, Pess, GR, & Quinn, TP (1999). Channel type and salmonid spawning distribution and abundance. *Canadian Journal of Fisheries and Aquatic Sciences*, *56* (3), 377-387.

Nex, F., & Remondino, F. (2014). UAV for 3D mapping applications: a review. *Applied Geomatics*, *6*(1), 1-15.

Nurhamidah, N., Rusman, B., & Istijono, B. (2018). A Raster-based model for flood inundation mapping on delta lowland. In *MATEC Web of Conferences* (Vol. 229, p. 03012). EDP

Parrish, DL, Behnke, RJ, Gephard, SR, McCormick, SD, & Reeves, GH (1998). Why aren't there more Atlantic salmon (*Salmo salar*)?. *Canadian Journal of Fisheries and Aquatic Sciences*, *55* (S1), 281-287.

Payne, B. A., & Lapointe, M. F. (1997). Channel morphology and lateral stability: effects on distribution of spawning and rearing habitat for Atlantic salmon in a wandering cobble-bed river. *Canadian Journal of Fisheries and Aquatic Sciences*, 54(11), 2627-2636.

Peterson, R. H. (1978). Physical characteristics of Atlantic salmon spawning gravels in some New Brunswick streams. *Fisheries and Oceans Canada, Biological Station. Fisheries and Marine Service Technical Report 785*. St. Andrews. New Brunswick.

Phillips, S. J., Dudík, M., & Schapire, R. E. (2017). *Maxent software for modeling species niches and distributions (Version 3.4.1)*. Available from url: http://biodiversityinformatics.amnh.org/open_source/maxent/. Accessed on 2020-6-5.

Rice, S. (1998). Which tributaries disrupt downstream fining along gravel-bed rivers?. *Geomorphology*, 22(1), 39-56.

Rimmer, D. M., Paim, U., & Saunders, R. L. (1984). Changes in the selection of microhabitat by juvenile Atlantic salmon (*Salmo salar*) at the summer–autumn transition in a small river. *Canadian Journal of Fisheries and Aquatic Sciences*, *41*(3), 469-475.

Roncoroni, M., & Lane, S. N. (2019). A framework for using small Unmanned Aircraft Systems (sUASs) and SfM photogrammetry to detect salmonid redds. *Ecological Informatics*, *53*, 100976.

Roussel, J. M., Cunjak, R. A., Newbury, R., Caissie, D., & Haro, A. (2004). Movements and habitat use by PIT-tagged Atlantic salmon parr in early winter: the influence of anchor ice. *Freshwater Biology*, *49*(8), 1026-1035.

Rushton, S. P., Hill, D., & Carter, S. P. (1994). The abundance of river corridor birds in relation to their habitats: a modelling approach. *Journal of Applied Ecology*, 313-328.

Rusnák, M., Sládek, J., Kidová, A., & Lehotský, M. (2018). Template for high-resolution river landscape mapping using UAV technology. *Measurement*, *115*, 139-151.

Samways, K. (2017). Unpublished data

Saska, M., Krajník, T., Faigl, J., Vonásek, V., & Přeučil, L. (2012, October). Low cost mav platform ar-drone in experimental verifications of methods for vision based autonomous navigation. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 4808-4809). IEEE.

Schlosser IJ. (1987). *A conceptual framework for fish communities in small warmwater streams*. In: Matthews WJ, Heins DC (eds) Community and evolutionary ecology of North American stream fishes. University of Oklahoma Press, Norman, pp 17–24

Schneider, K. N., & Winemiller, K. O. (2008). Structural complexity of woody debris patches influences fish and macroinvertebrate species richness in a temperate floodplain-river system. *Hydrobiologia*, 610 (1), 235-244.

Schumm, S. A. (2007). *River variability and complexity*. Cambridge University Press.

Srivastava, V., Lafond, V., & Griess, V. C. (2019). Species distribution models (SDM): applications, benefits and challenges in invasive species management. *CAB Reviews*, *14*(020), 1-13.

Sten, J., Lilja, H., Hyväluoma, J., Westerholm, J., & Aspnäs, M. (2016). Parallel flow accumulation algorithms for graphical processing units with application to RUSLE model. *Computers & Geosciences*, *89*, 88-95.

Tang, L., & Shao, G. (2015). Drone remote sensing for forestry research and practices. *Journal of Forestry Research*, *26*(4), 791-797.

Têtu, C., Mitchell, S., MacInnis, C., & Taylor, B. R. (2016). Restoration of a Nova Scotia stream to enhance Atlantic salmon provides few benefits to benthic invertebrates. *Proceedings of the Nova Scotian Institute of Science (NSIS)*, 48(2), 211.

Thorstad, E. B., Økland, F., Aarestrup, K., & Heggberget, T. G. (2008). Factors affecting the within-river spawning migration of Atlantic salmon, with emphasis on human impacts. *Reviews in Fish Biology and Fisheries*, *18*(4), 345-371.

Thorstad, E. B., Whoriskey, F., Rikardsen, A. H., & Aarestrup, K. (2011). Aquatic nomads: the life and migrations of the Atlantic salmon. *Atlantic salmon ecology*, *1*(6).

Trzcinski, M. K., Gibson, A. J. F., Amiro, P. G., Randall, R. G., & Burlington, O. (2004). Inner Bay of Fundy Atlantic salmon (*Salmo salar*) critical habitat case study. *Science*, *2*, 4A2.

Ullman, S. (1979). The interpretation of structure from motion. *Proceedings of the Royal Society of London. Series B. Biological Sciences*, *203*(1153), 405-426.

Vadas, R. L., & Orth, D. J. (1998). Use of physical variables to discriminate visually determined mesohabitat types in North American streams. *Rivers-Fort Collins*, *6*, 143-159.

Van Zyll De Jong, M. C., Cowx, I. G., & Scruton, D. A. (1997). An evaluation of instream habitat restoration techniques on salmonid populations in a Newfoundland stream. *Regulated Rivers: Research & Management: An International Journal Devoted to River Research and Management*, *13*(6), 603-614.

Verspoor, E. (2005). Regional differentiation of North American Atlantic salmon at allozyme loci. *Journal of Fish Biology, 67*, 80-103.

Ward, T. A., Tate, K. W., Atwill, E. R., Lile, D. F., Lancaster, D. L., McDougald, N., & Frost, W. E. (2003). A comparison of three visual assessments for riparian and stream health. *Journal of Soil and Water Conservation*, *58*(2), 83-88.

Westoby, M. J., Brasington, J., Glasser, N. F., Hambrey, M. J., & Reynolds, J. M. (2012). 'Structure-from-Motion'photogrammetry: A low-cost, effective tool for geoscience applications. *Geomorphology*, *179*, 300-314.

Wohl, E. (2005). Compromised rivers: understanding historical human impacts on rivers in the context of restoration. *Ecology and Society*, *10*(2).

Woodget, A. S., Carbonneau, P. E., Visser, F., & Maddock, I. P. (2015). Quantifying submerged fluvial topography using hyperspatial resolution UAS imagery and structure from motion photogrammetry. *Earth Surface Processes and Landforms*, *40*(1), 47-64.

Zinke, P., & Flener, C. (2013). Experiences from the use of unmanned aerial vehicles (UAV) for river bathymetry modelling in Norway. *Vann*, *48*, 351-360.