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Evaluating Methods to Describe Individual Substrate Size Classes in River Habitats

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Evaluating Methods to Describe Individual Substrate Size Classes in River Habitats

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CONTENTS

ABSTRACT

The Oregon Department of Fish and Wildlife's Aquatic Inventories Program has been developing methods that describe aquatic habitats across mainstem river environments that are generally not wadeable. During the summer of 2018 over the course of 16 survey days, we sampled over 65 kilometers of mainstem habitat in the Siletz River upstream of estuary and tidal influence. We identified seven distinct reaches and 389 independent habitat units. Sampling methods consisted of tributary stream techniques (wadeable) that rely on ocular observations and physical habitat measurements. We returned in the winter of 2019 and over the course of five days, resurveyed the same bounds of each defined reach using a 1199CI HD Humminbird side-scan sonar that was set to record continuous imagery. The images were visually assessed within the bounds of individual habitat units to describe streambed features using a modified Wolman Pebble Count. We summarized the results of each method at the reach scale to describe the efficiency and effectiveness of ocular estimation versus imagery from a side-scan sonar and the accuracy of streambed features captured from sonar imagery. We found that using a sonar to describe substrate size classes was a more efficient way to collect field data, but after including data processing and analysis time, both methods were similar in overall time. To assess the accuracy of sonar imaged streambed features, we used a simple linear regression to assess whether percent substrate from ocular estimates differed from sonar imagery. Individual substrate class adjusted R^2 results across reaches ranged from 0.64 to 0.95 and p-values were all less than 0.05. When substrate classes were modeled within reaches, adjusted R^2 results ranged from 0.50 to 0.99 and p-values were less than 0.05 in four out of the seven reaches. These findings suggest that the use of a side-scan sonar within river habitats describes individual substrate types consistent with results of ocular estimation with less effort in the field. The results of this report were used to create a key for describing individual substrate types when viewed on sonar imagery to improve future mainstem river survey accuracy and efficiency. We hope these methods will help integrate mainstem river habitat information with current data from tributary streams to give ODFW a complete picture of population-scale habitat availability and condition.

INTRODUCTION

Field biologists, volunteers, and summer interns walk headwater creeks every year, gathering data about stream habitats. These are generally first through third order streams that are wadeable at the time of a survey. Numerous peer-reviewed protocols exist, giving agencies and individuals various sampling options to address their objectives (Hankin and Reeves 1988; Hawkins et al. 1993; Rosgen 1985; Reeves et al. 2006; Moore et al. 2007). These habitat data are used to assess status and trend of aquatic habitats and other ecological associations, like fish use and assemblages (Nickelson and Lawson 1998; Burke et al. 2010; Flitcroft et al. 2012; Anlauf-Dunn et al. 2014; Miller et al. 2016). In contrast, fourth through sixth order river habitats across the Pacific Northwest have been largely understudied, and when sampling does occur, it is often focused primarily along bank margins or within estuarine environments (Beamer and Henderson 1998; Quinones and Mulligan 2005; Brophy 2007; Beechie et al. 2017; USEPA 2017). A substantial constraint to sampling mainstem rivers has been the inability to consistently describe submerged features due to water depth, turbidity, or the overall scale of the river surface area. Recently, sampling techniques have emerged using side-scan sonar technology in place of traditional visual methods to capture streambed habitat features in non-wadeable environments (Anima et al. 2007; Keaser and Litts 2010; Kaeser et al. 2013; Parker et al. 2020).

The Aquatic Inventories Program has been developing methods that utilize non-traditional techniques to capture habitat condition within mainstem rivers and non-wadeable environments. These methods focus on two primary protocols; a unit-scale classification system (Moore et al. 2007) and one that employs a side imaging sonar as described in Kaeser and Litts 2010. We are applying a flexible approach in how heavily we weigh on each of these depending on seasonal conditions and habitat type.

Because we wanted to use two different protocols, across two sampling seasons with variable environmental conditions, we initiated a study across mainstem habitat in the Siletz River basin. We had two primary objectives; (1) describe the efficiency of ocular estimation versus imagery from a side-scan sonar, and (2) compare the effectiveness of describing streambed features captured from sonar imagery during winter conditions with those ocularly estimated during summer conditions. We hypothesized that sonar imagery can be used to estimate the quantity of individual substrate classes across mainstem river habitats. The purpose of this report is to describe the efficiency and effectiveness of methods developed for mainstem river and non-wadeable habitat sampling while also addressing the question of substrate imagery accuracy.

METHODS

Study Area

The Siletz River is formed by the confluence of the North and South Forks near Valsetz, Oregon. Approximately 2.5 kilometers downstream of the confluence is Siletz Falls which serves as the location for the start of non-wadeable habitat. From there the river flows 108 km to the Pacific Ocean near Lincoln City, Oregon (Figure 1). The underlying lithology of the Siletz basin is primarily marine sandstone and basaltic volcanic rock (Spies et al. 2002; Strickland et al. 2018). The regional climate is heavily influenced by marine processes and winter temperatures that generally fluctuate between 5° and 15° C (Spies et al. 2002). Precipitation, primarily rain, generally ranges from 100 cm (inland areas) to 200 cm (coastal areas) per year. Land ownership in the basin is primarily a mix of private and federal lands, with private forest dominating the riparian areas (Strickland et al. 2018).

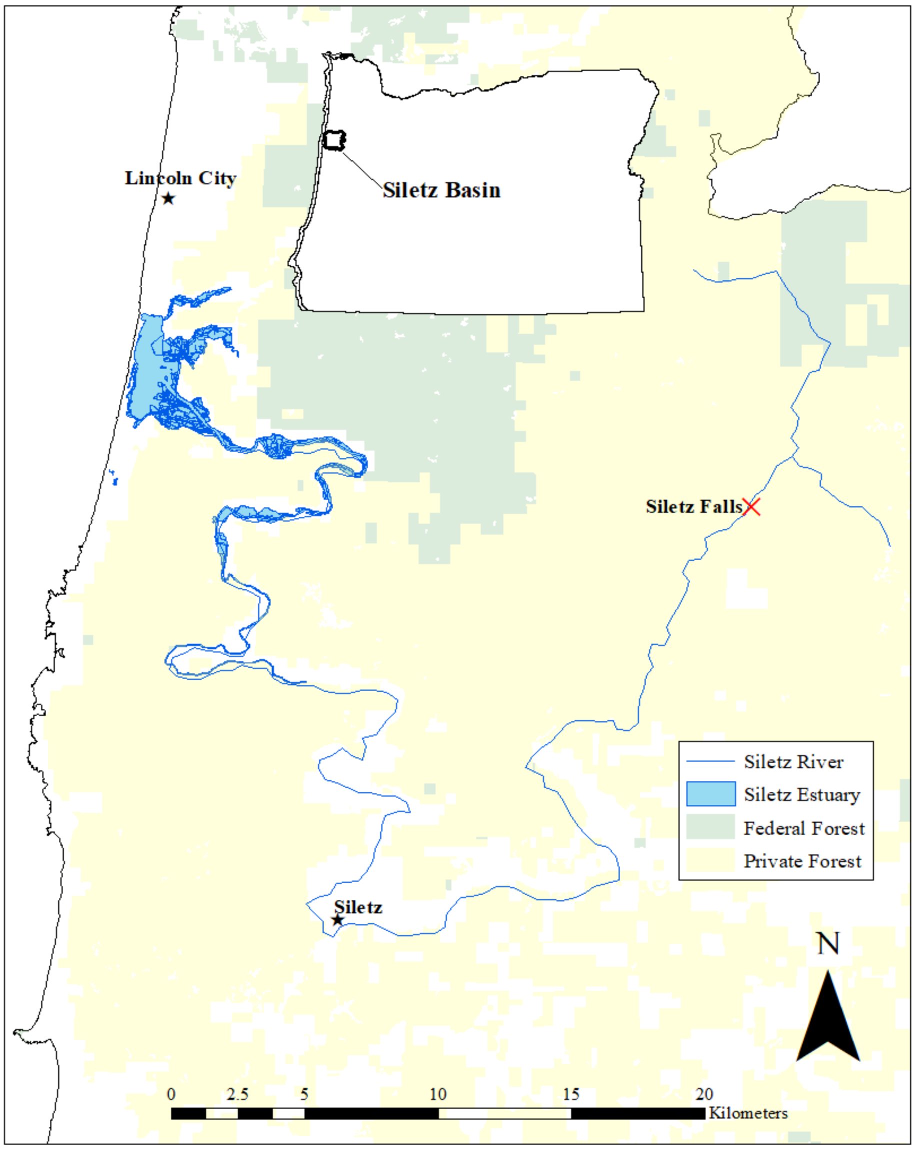

Figure 1. Siletz River basin.

Summer Physical Habitat Survey

During the summer of 2018, we surveyed over 65 kilometers of the Siletz River mainstem habitat. This effort started at the confluence with Elk Creek, located approximately two kilometers downstream of Siletz Falls, and ended at the confluence with Cedar Creek, located at the head of tidal influence. We started at Elk Creek due to safety concerns with boat launching below Siletz Falls. These surveys took place during base flow conditions when river conditions are such that we had adequate visibility. We used sampling techniques described in Moore et al. 2007 when measuring 521 independent habitat units and seven distinct reaches over the course of 16 days (Figure 2). Because this report is focused on a methods comparison in mainstem habitat that is not wadeable, we excluded all secondary channel habitat units in our analysis. Reaches were differentiated by channel and valley formation, major land use changes, or tributaries contributing more than 15% flow to the Siletz River. Within reaches we subdivided mainstem habitat into unit classes consisting of fast water, pools, and steps. Steps were differentiated from fast water by a vertical gradient break with a length less than the width of the active channel (Moore et al. 2007). We identified 389 individual mainstem habitat units. Within individual units we measured habitat area, cover attributes, and visually estimated individual substrate classes (silt, sand, gravel, cobble, boulder, and bedrock).

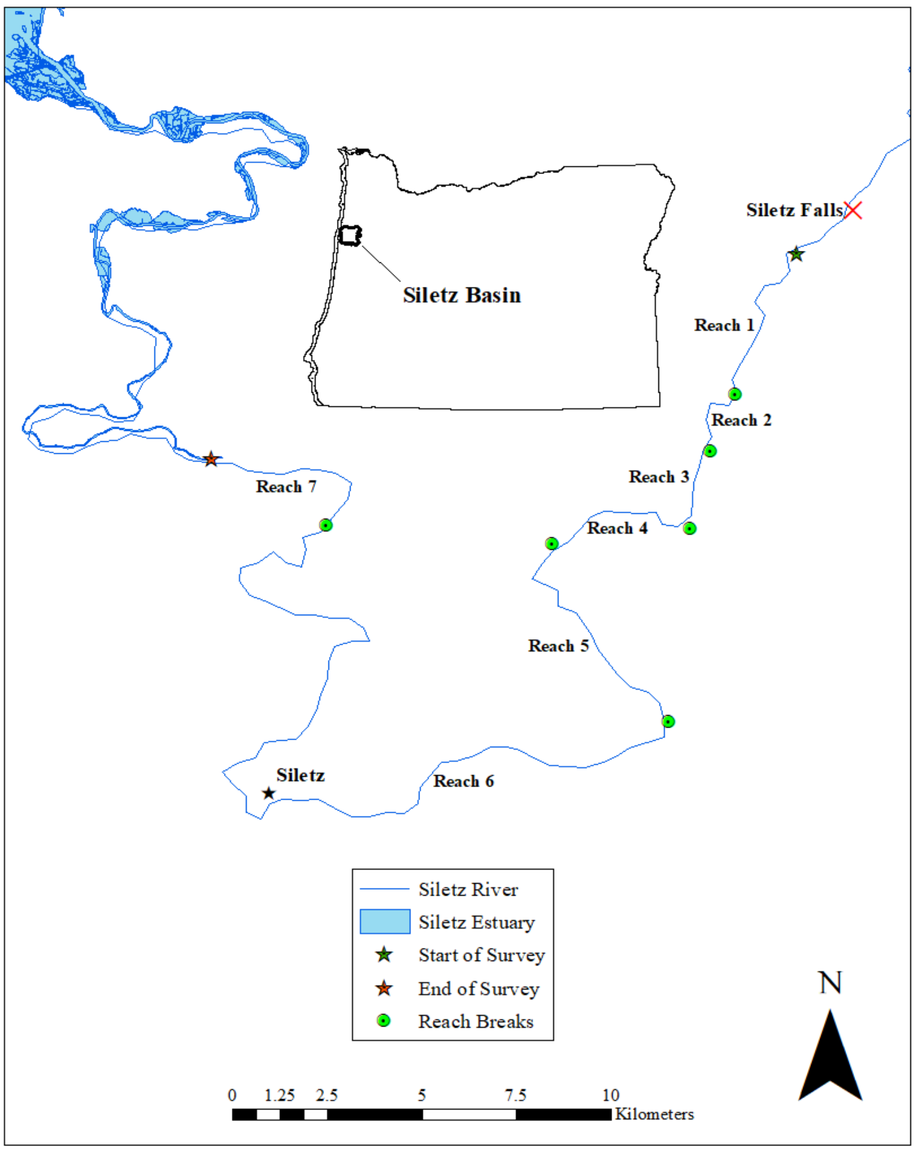

Figure 2. Siletz River survey boundaries and reach locations.

Winter Sonar Imagery Survey

Surveyors returned to the same reaches during the winter of 2019 (February and March) with a 1199CI HD Humminbird side imaging system set to obtain continuous sonar data. The sonar transducer was positioned on the bow of a rubber raft or drift boat via a custom mount and set at an operating frequency of 455 kHz. The side beam range was set relative to channel width and did not exceed 35 meters. Data were recorded while maintaining a mid-channel position at approximately 8.0 km/h. Surveys were conducted during normal winter flow conditions. At these flows visibility was normally inadequate for ocular estimation across most wetted areas. We were able to map all mainstem habitats across the same reaches over five days.

Substrate Quantification – Physical Habitat Survey

The Aquatic Inventories Project (AQI) estimates streambed features, based on substrate size class, as a percent distribution of the wetted streambed area. In instances of dry streambeds, those percentages are distributed across the entire active channel (a.k.a. bank-full width). These percentages are derived from ocular observations from trained field biologists. The AQI protocol characterizes substrate based on size classes described in Table 1.

Table 1. Substrate size classes.

Size Class	Size Range (mm)
Silt/Organic	Undefined, particles
Sand	< 2
Gravel	2 – 64
Cobble	64 – 256
Boulder	> 256
Bedrock	Undefined, continuous

Data were collected within individual habitat units and summarized at the reach scale. Particles <2 mm were described as either silt and fine organic matter, or sand depending on texture and dispersal in the water column. Surveyors split these into two distinct substrate classes, but during data processing these were grouped into one substrate class, percent fines.

Substrate Quantification – Sonar Imagery Survey

We sub-sampled each reach by randomly selecting every fifth pool and fast water type habitat unit (glides, riffles, rapids, or cascades) as we moved from upstream to downstream. If the imagery from a selected habitat unit was too distorted to accurately describe the substrate, we selected the closest adjacent pool or fast water. All steps were excluded due to image distortion. Across reaches, we sub-sampled 49 individual habitat units or 13% of the available mainstem habitat. Of those, 28 were pools and 21 were fast water types. Our goal was to sub-sample 15% of the mainstem habitat.

We used SonarTRX software (Leraand Engineering Incorporated, Honolulu, Hawaii, USA) to generate projected mosaics from the side-scan sonar continuous imagery recordings. Imagery data were assembled within the bounds of each pre-defined reach and projected in ArcGIS 10.7.1 (ESRI, Redlands, CA). Within the bounds of individual habitat units that were identified during the summer surveys, we used a Wolman Pebble Count approach (Wolman 1954) by creating 10 evenly distributed transects across the longitudinal thalweg profile overlayed on imagery obtained from the sonar. One particle (substrate type) was described at each of 10 evenly spaced intervals (substrate points), based on channel width, within each transect line (Figure 3). This created a total of 100 particle measurements that were assigned to substrate size classes, as a percent distribution of the wetted streambed area, for each of the 49 subsampled habitat units. Transects started at the wetted edge of the channel margin. Dry streambed areas were not sampled due to the inability of the sonar to gather imagery.

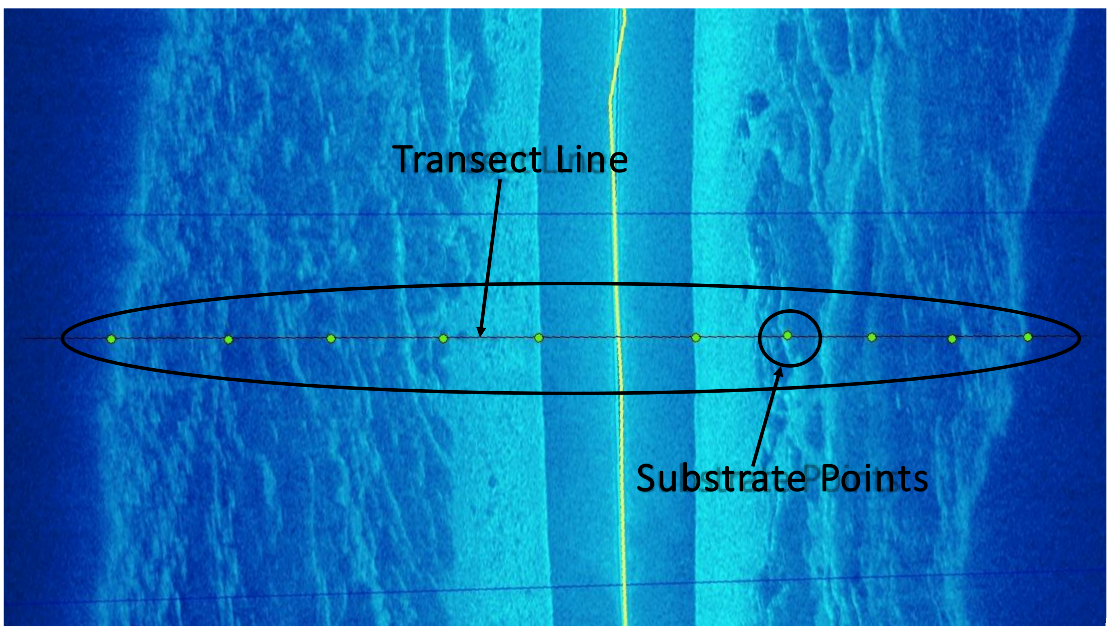

Figure 3. Depiction of single transect line and substrate points over sonar imagery.

Methods Comparison

Individual substrate classes (as a percentage of the wetted area) were averaged across reaches for both methods. We used R software (R Development Core Team 2006) to compare substrate class results within individual reaches and individual substrate class results across reaches. A simple linear regression ($Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$) was used to assess whether percentages from individual substrate size classes from ocular estimates obtained during the summer surveys differed from those derived from the Wolman Pebble Count obtained from the winter sonar imagery. Our response variables were (1) the individual substrate size classes, and (2) the individual reaches. The intent of this approach was to test for method variability between the substrate size classes and at the summarized reach scale.

RESULTS

Physical Habitat Survey

Across all reaches, mainstem habitat consisted of 42% pools, 53% fast water, and 5% steps. These were similar within reaches (Table 2). Percent of fines and gravel were greatest in reach seven, the furthest downstream reach. Percent boulder was greater in the upper half of the basin and lowest in reaches six and seven. Percent bedrock was lowest in reaches two, three, and seven. Percent cobble was lowest in reach seven and highest in reach two.

Table 2. Summarized habitat classes and substrate percentages within each reach from the physical habitat survey.

Reach	% Pools	% Fast Water	% Fines	% Gravel	% Cobble	% Boulder	% Bedrock
1	45.50	49.09	7.22	26.08	21.84	22.92	21.94
2	54.80	38.71	14.68	26.69	34.06	16.49	8.08
3	37.50	58.33	1.97	13.53	28.51	49.04	6.95
4	40.50	57.14	11.43	18.66	24.66	26.82	18.43
5	35.80	58.49	10.45	21.76	32.24	14.11	21.45
6	40.60	53.75	15.75	26.94	27.06	8.81	21.44
7	50.00	45.83	21.36	45.40	16.74	4.49	12.02

Sonar Imagery Survey

We generated sonar imagery across all reaches, however, turbulent flow and velocity around obstructions caused the sonar transducer to move in a vertical or horizontal path. These complex habitats created enough image distortion that we subsampled more pool habitat than fast water areas. We did not evaluate the imagery for step habitat. Across all reaches, sub-sampled habitat consisted of 57% pools and 43% fast water (Table 3). We subsampled 11% of the mainstem habitat in reach one, 13% in reach two, 13% in reach three, 19% in reach four, 9% in reach five, 12% in reach six, and 17% in reach seven. Percent of fines and gravel were greatest in reach seven (Table 3). Percent boulder was highest in reach three and lowest in reaches six and seven. Percent bedrock was lowest in reach three and highest in reach six. Percent cobble was lowest in reach seven and highest in reach two.

Table 3. Summarized habitat classes and substrate percentages within each reach from the sonar imagery.

Reach	% Pools	% Fast Water	% Fines	% Gravel	% Cobble	% Boulder	% Bedrock
1	66.67	33.33	6.67	22.33	27.50	19.17	24.33
2	75.00	25.00	11.25	27.00	34.50	18.00	9.25
3	33.33	66.67	1.00	13.00	31.67	50.67	3.67
4	50.00	50.00	10.00	18.13	23.50	31.25	17.13
5	60.00	40.00	5.60	20.00	27.00	19.80	27.60
6	57.89	42.11	9.90	22.16	27.47	9.26	30.68
7	50.00	50.00	21.00	47.25	13.50	6.50	11.75

Methods Comparison

We compared substrate results from the summer ocular estimates with the sonar imagery across sampling reaches using a simple linear regression. The model was run for each substrate class across reaches. R^2 values ranged from 0.64 (% Cobble) to 0.95 (% Gravel and % Boulder) (Table 4).

Table 4. Method comparison across reaches for individual substrate size classes. Response variable = individual substrate classes.

Substrate Class	Residual DF	F-statistic	p-value	Adjusted R^2
Fines	5	40.91	0.0014	0.8693
Gravel	5	122.0	0.0001	0.9527
Cobble	5	11.76	0.0187	0.6419
Boulder	5	117.6	0.0001	0.9510
Bedrock	5	46.73	0.0010	0.8840

The greatest variability across substrate classes occurred with percent cobble (Figure 4). P-values were less than 0.05 indicating a strong relationship between the two methods.

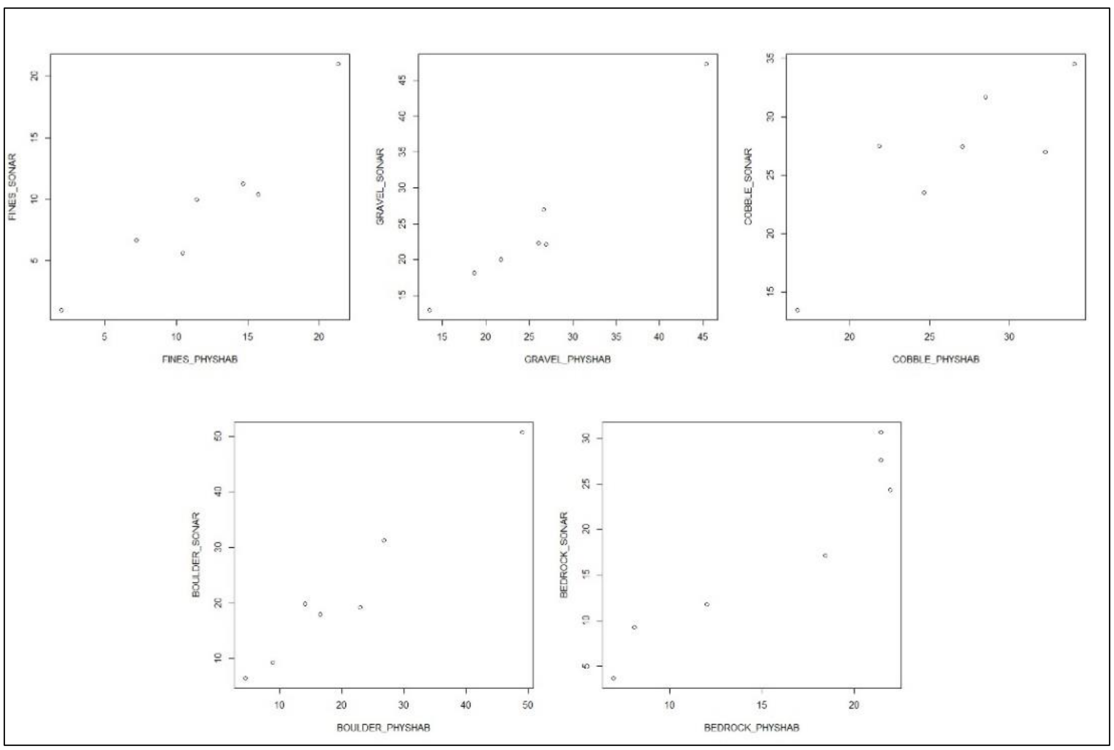

Figure 4. Substrate plots across reaches comparing results from sonar imagery (y axis) and the physical habitat survey (described as PHYSHAB on the X axis).

We also ran the model for each substrate class within individual reaches. R^2 values ranged from 0.50 (Reach 5) to 0.99 (Reach 3), and p-values were less than 0.05 across four of the seven reaches (Table 5).

Table 5. Method comparison for substrate classes within individual reaches. Response variable = individual reaches.

Reach	Residual DF	F-statistic	p-value	Adjusted R^2
1	3	8.851	0.0588	0.6625
2	3	88.84	0.0027	0.9545
3	3	453.8	0.0002	0.9912
4	3	50.32	0.0058	0.9250
5	3	5.067	0.1098	0.5042
6	3	5.353	0.1037	0.5211
7	3	176.1	0.0009	0.9777

The results suggest that the two methods used to describe streambed features at the reach scale were similar, but more variability was observed in reaches one, five, and six compared to all others (Figure 5). Interestingly, these were also the three reaches with the lowest percent of mainstem habitat that was sub-sampled due to image distortion, and highest percent of sub-sampled pool habitat relative to the physical habitat survey.

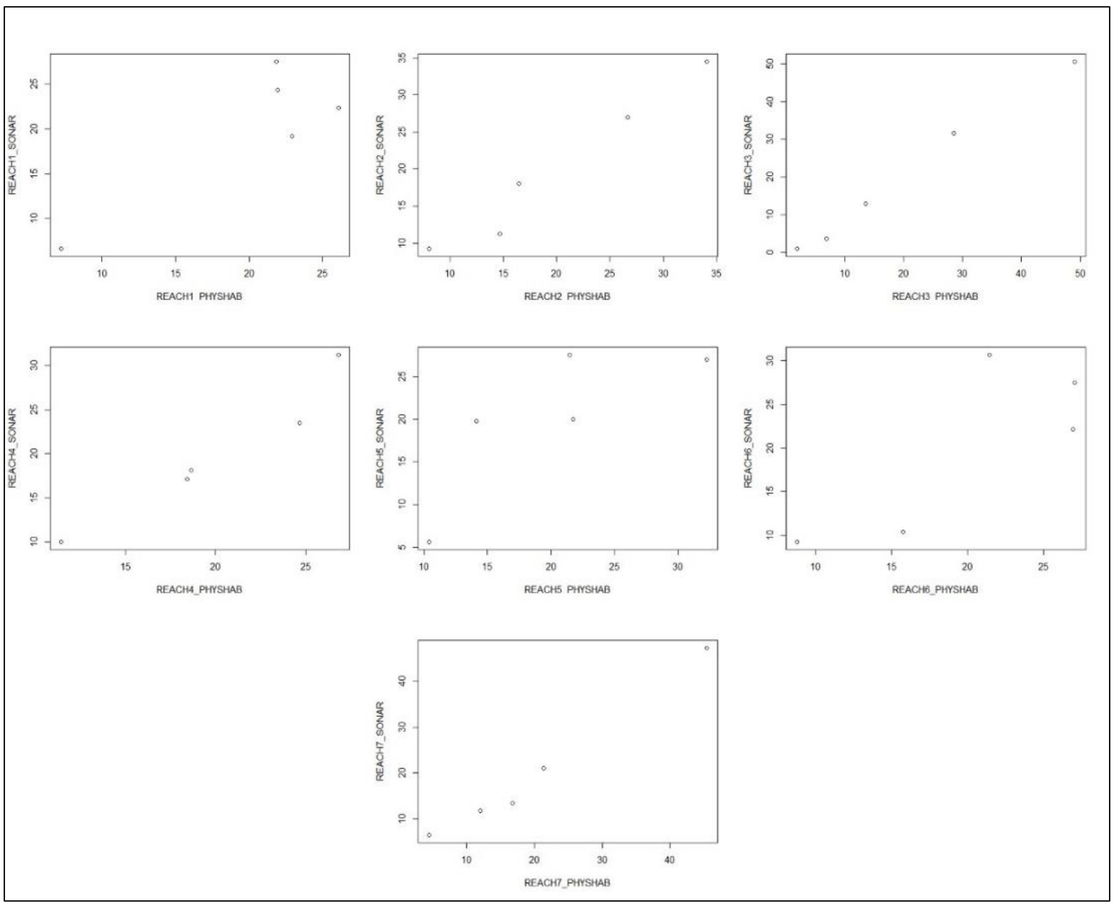

Figure 5. Plots within reaches comparing substrate class results from sonar imagery (y axis) and the physical habitat survey (described as PHYSHAB on the X axis).

DISCUSSION

Results of the linear regression showed that the use of sonar imagery can sufficiently describe individual substrate classes at the reach scale. These results were like other studies comparing visual and measurement-based sediment techniques (Conroy et al. 2016; McHugh and Budy 2005; Sutherland et al. 2010). While these studies were able to show the relative accuracy of visual estimates for attributes (i.e., surface fines or cobble embeddedness), study results from Strickland and Davies (2020) showed that trained field surveyors using Aquatic Inventories methods can accurately estimate the quantity of individual substrate classes using ocular observation techniques in headwater streams. Our current study was different from these because it showed that individual streambed features could be described in a river environment similar to that of Kaeser et al. (2013) and Graham et al. (2017). Our data are unique in that we used sonar imagery to accurately describe the percent of individual substrate size classes across complex non-wadeable river habitats relative to visual estimates.

One of the primary questions going into this study was which method was the most time efficient using a two-person survey crew: a physical habitat survey using traditional ocular observation techniques or the use of a side-scan sonar? We have previously shown the sonar method to be efficient and capable of describing features in slough type habitats (Strickland et al. 2019) and now the hybrid approach described specific attributes accurately in turbulent flow, sinuous channels, and around complex obstructions (wood, boulders, and gradient breaks). Surveying the Siletz River required 16 field days using physical habitat methods to completely sample all areas, compared to only five days using the sonar method. This would suggest using the side-scan sonar would be the most efficient method, but two primary issues arose that need to be addressed before committing solely to this approach; (1) image distortion associated with complex and technical habitat, and (2) data processing time.

When we viewed the sonar imagery, turbulent flow and gradient breaks around obstructions forced us to sub-sample a higher percentage of pool habitat across reaches relative to what was described during the summer physical habitat survey. This bias towards slower moving, depositional habitat may have influenced the variability observed when comparing methods at the reach scale. When we combined the sonar field time and time spent data processing, the total time spent on the sonar method was very similar to the total time spent on the physical habitat methods. This is something that will have to be taken into consideration if future efforts do not allow for sub-sampling or require finer scale (i.e., individual unit level) results.

We are confident in the results of this study, but repeatability was not tested, and we are assuming the imagery would be interpreted similarly by different users. This assumption is based on previous resurvey efforts by the Aquatic Inventories Program both within seasons (Anlauf-Dunn and Jones 2012; Strickland and Constable 2022), and across seasons (Romer et al. 2008). To improve image quality within all habitat types, multiple sonar passes across stream flow heights may be required to find optimal conditions. This assumption is strongly supported by results reported in Kaeser et al. (2013). During recent efforts, when ideal images were captured, we developed a sonar imagery substrate key (Appendix) that illustrates each substrate type to aid in understanding the images captured by the sonar recording. Our goal will be to eliminate any potential surveyor-to-surveyor variability and improve data processing efficiency by using computer vision tools to describe the captured imagery. We hope these tools will improve precision at the habitat unit scale, improve overall data quality, and allow for the potential to utilize existing habitat quality models. These models, such as the Habitat Limiting Factors Model (Nickelson 1998) and the HabRate model (Burke et al. 2010), would be used to evaluate adult salmonid spawning and juvenile rearing availability and condition.

Describing status and having a repeatable protocol in place to evaluate trend across non-wadeable habitats has gained importance with the publication of recent conservation and recovery plans that emphasize stream habitat as a key limiting factor to the recovery of listed species (ODFW 2007; ODFW 2010; ODFW 2021). Priority is generally directed towards complex pools and off-channel winter rearing habitat for juvenile coho salmon (*Oncorhynchus kisutch*), and adequate adult salmonid (*Oncorhynchus* spp.) spawning habitat. The Oregon Department of Fish and Wildlife's Aquatic Inventories Program has described the quantity, distribution, and trends of these habitats in wadeable streams ($\leq 4^{th}$ order) (Anlauf et al. 2009; Anlauf-Dunn and Jones 2012; Strickland et al. 2018; Strickland and Constable 2022), but until recently has not had the ability to expand data collection to mainstem, non-wadeable habitat. We hope these methods will help integrate non-wadeable data with current habitat data from wadeable stream surveys (Strickland et al. 2018; Crowley and Strickland 2022) to give ODFW a complete picture of population-scale habitat.

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APPENDIX

Aquatic Inventories Program: Sonar Imagery Substrate Key

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The goal of this visual reference key is to aid in the understanding of how to interpret each type of substrate as it appears on sonar imagery. While it is important to understand the most efficient and effective means to capture habitat features and the different elements of a sonar image, this is not intended to be a protocol for conducting side-scan sonar surveys. Please refer to Kaeser and Litts (2013) for an in-depth description of sonar applications.

A Humminbird 1199 CI HD Side Scan Sonar with a forward-mounted transducer was used to collect sonar images for this visual reference key. The transducer was attached to a custom-made tiltable bracket to be easily adjustable when navigating shallow and obstacle-laden river sections. The Side Scan Sonar was mounted to a frame on a raft, Jon boat, or a drift boat depending on the scale and complexity of the river surveyed. The imagery was collected using a continuous sonar recording. The side-scan sonar creates a streaming data file of the survey and saves it to a micro-SD card. We used SonarTRX software (Leraand Engineering Incorporated, Honolulu, Hawaii, USA) to generate projected mosaics from the side-scan sonar continuous imagery recordings.

Side-scan sonar measures the intensity or the amplitude of returning acoustic signal pulses and translates the differences in amplitude into differences in pixel tone in the developing sonar image (Kaeser and Litts 2010). These tonal differences are due to differences in substrate composition. Substrates are defined based on a size range established by the Wentworth Grading Scale (Wentworth 1922) (Table 1).

Table 1. Evaluated substrate types based on Wentworth Scale (Wentworth 1922)

Silt and fine organic matter	.002-.063mm
Sand	.064-2.0mm
Gravel	2.0-64mm (pea-baseball)
Cobble	64-256mm (baseball-bowling ball)
Boulder	256->630mm
Bedrock	Consolidated rock

Sonar images are interpreted using texture, tone, shape, pattern, and association to distinguish and classify substrate type. In Figure 1 below, we see an aerial view of the Salmon River estuary (A). When sonar imaging is applied to the highlighted area (B), it becomes clear that two distinct substrate types are present in the riverbed.

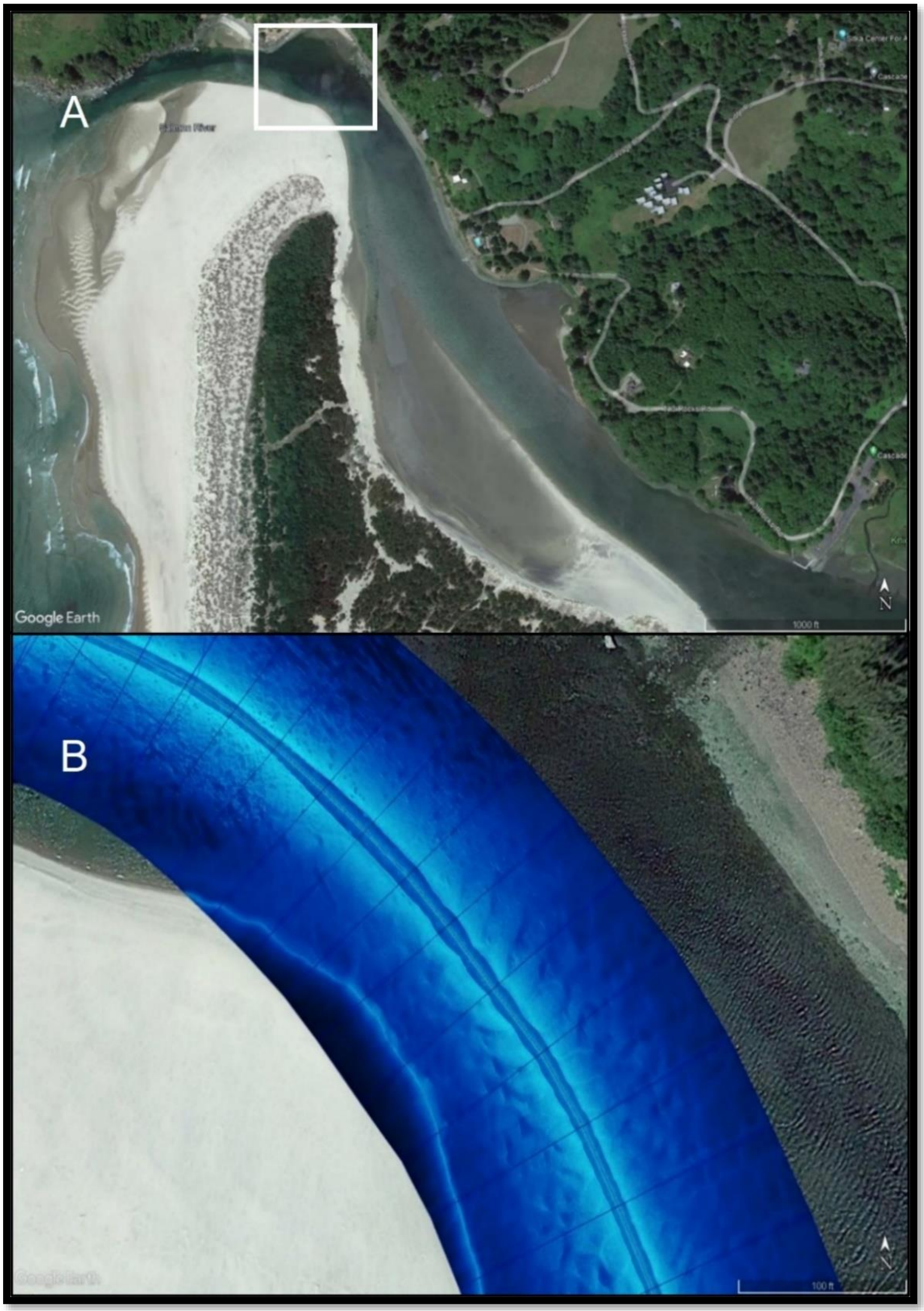

Figure 1. Aerial view (Google Earth) of Salmon River estuary (Oregon) with sonar imagery.

When viewing the substrate imagery, darker tones represent hard, reflective surfaces like bedrock and large boulders. The granular static feedback tones represent cobble and gravel substrates, with the larger grains representing cobbles and the finer-grained pixels representing gravels. The smooth, brighter tones often represent finer substrates like sand, silt, and mud.

Zooming in on the area outlined in the Salmon River estuary, we see two distinct substrate types; sand, and boulders, stand out by paying attention to the sonar image's textures, tones, patterns, and shapes (Figure 2). Finer substrates such as sand are heavily influenced by the river currents and will move around easier than heavier substrates. Often this will cause a rippled texture resembling desert dunes that have been moved and shaped by the wind. Near the top of Figure 2, the texture changes from smooth ripples to a grainier composition resembling rough sandpaper. It becomes apparent that there is a conglomeration of boulders nestled within the sand.

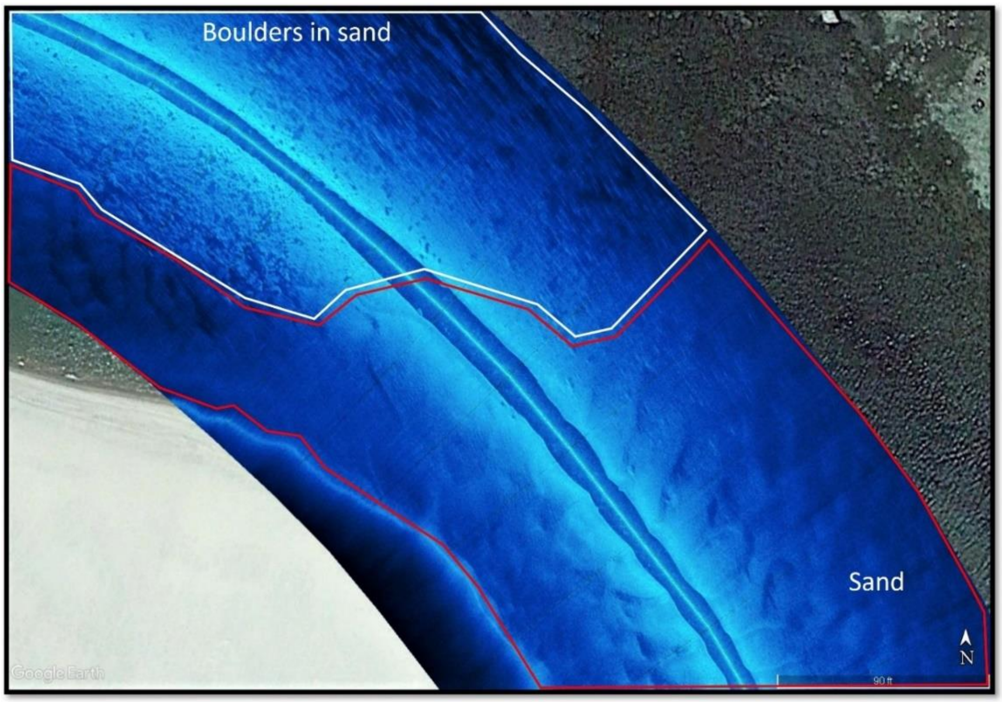

Figure 2. Aerial view of Salmon River estuary (Oregon) sonar imagery and substrate differences. Google Earth background image.

Another observational clue to consider when interpreting sonar images is the surrounding landscape. The figure above shows that this is a coastal environment influenced by a large sandy beach. So, it is not surprising that the river bottom is primarily comprised of the same material by association. The following figures and pages will break down each substrate type and composition and point out some visual clues that aid in identifying and quantifying substrates when interpreting the sonar image.

Silt and Fine Organic Matter

In figure 3 (below), we identify the substrate as mud from the Google Earth satellite view of the Columbia Slough, near Portland, Oregon.

Figure 3. Aerial imagery (Google Earth) of silt and fine organic matter in the Columbia Slough, Oregon.

When the sonar recording is applied to the image, we can easily identify the scoured channel through the mud-like substrate (Figure 4, A). The organic substrates of silt and fine organic matter read as a smooth texture with a primarily homogenous tone that comprises the vast majority of slough bedload area (Figure 4, B).

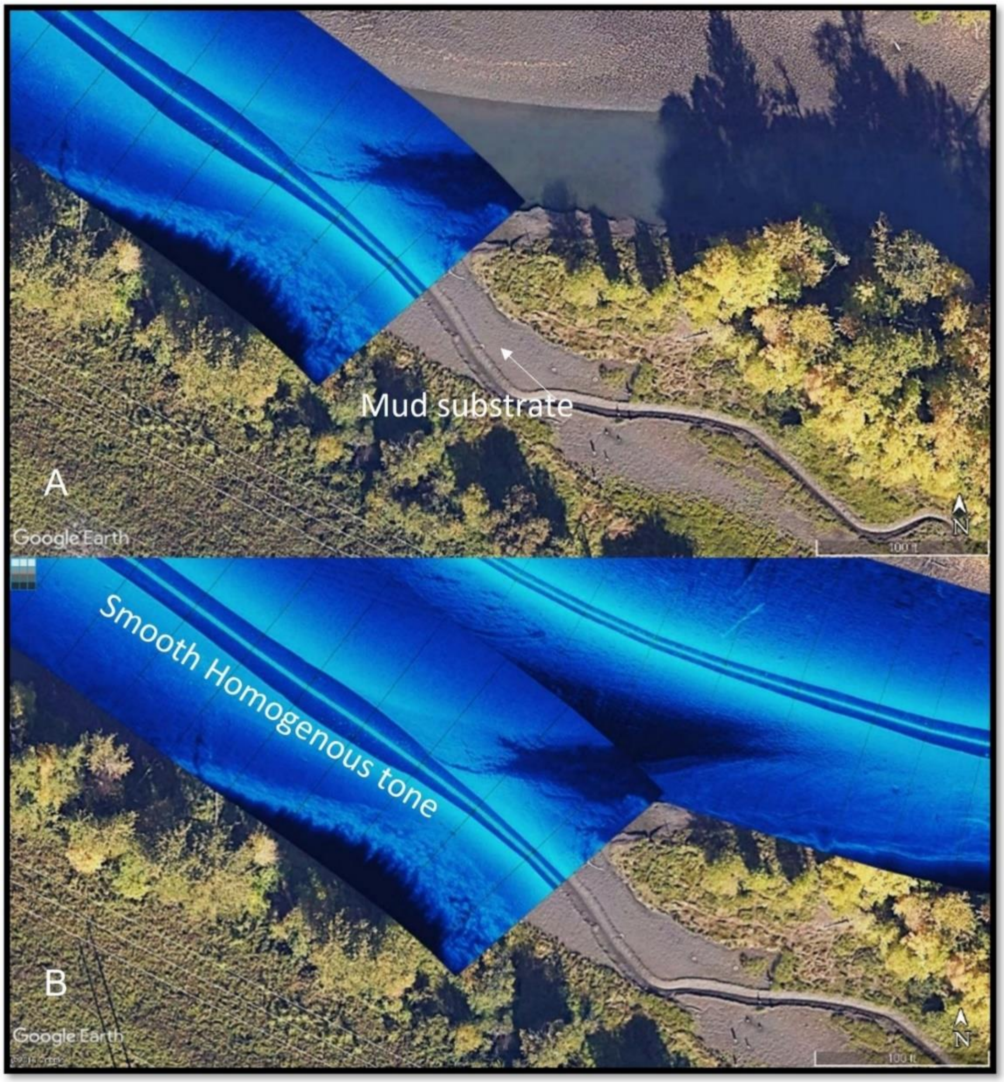

Figure 4. Aerial imagery (Google Earth) with sonar imagery overlay of silt and fine organic matter in the Columbia Slough, Oregon.

The Google Earth image in Figure 5 is from July of 2018 and shows what remains of the water channel at low water. The river bottom is composed mainly of silt and fine organic matter, with areas of dense vegetation encroaching along the channel margins. The sonar image was recorded in May 2019 when the channel was at bank full.

Figure 5. Aerial imagery (Google Earth) of Columbia Slough, Oregon from July 2018.

In the sonar image (Figure 6), the sediment in the channel remains unchanged from the year prior. The silt and fine organic matter are uniform in tone and texture, while the vegetation along the margins has a much more porous texture.

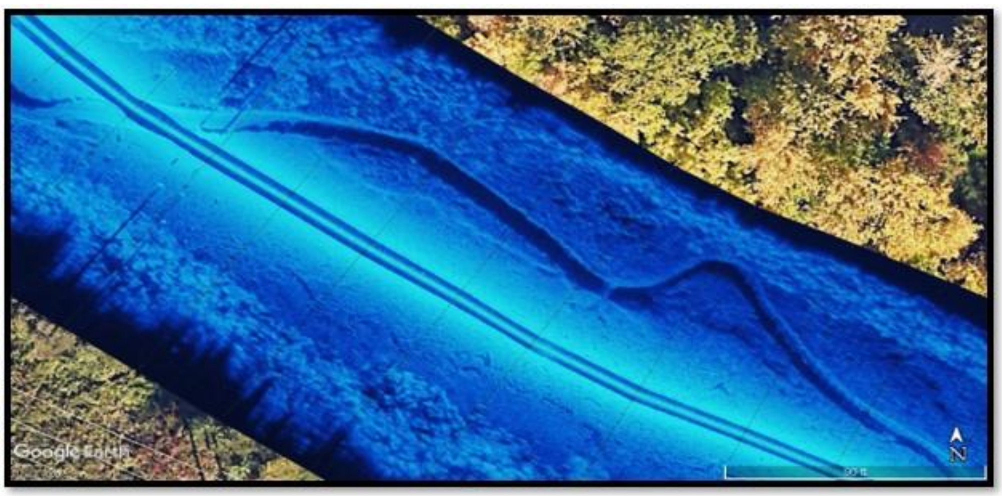

Figure 6. Sonar imagery of Columbia Slough, Oregon from May 2019. Google Earth background image.

Sand

Figure 7 represents a section of the Salmon River estuary entirely made up of sand. Sand differs in how it reads on the sonar compared to silt and mud in that it will often appear to be rippled in its texture. Sand substrates are easily affected by river currents and form wave-like patterns resembling windswept dunes. Sand ripples can be observed by the naked eye in top section (A). When one channel of the sonar recording is applied over the top of the satellite image, the sand ripples can be seen in more detail (B). When both channels of the sonar recording are applied, a consistent pattern of rippled textures highlights and defines the sand substrate (C).

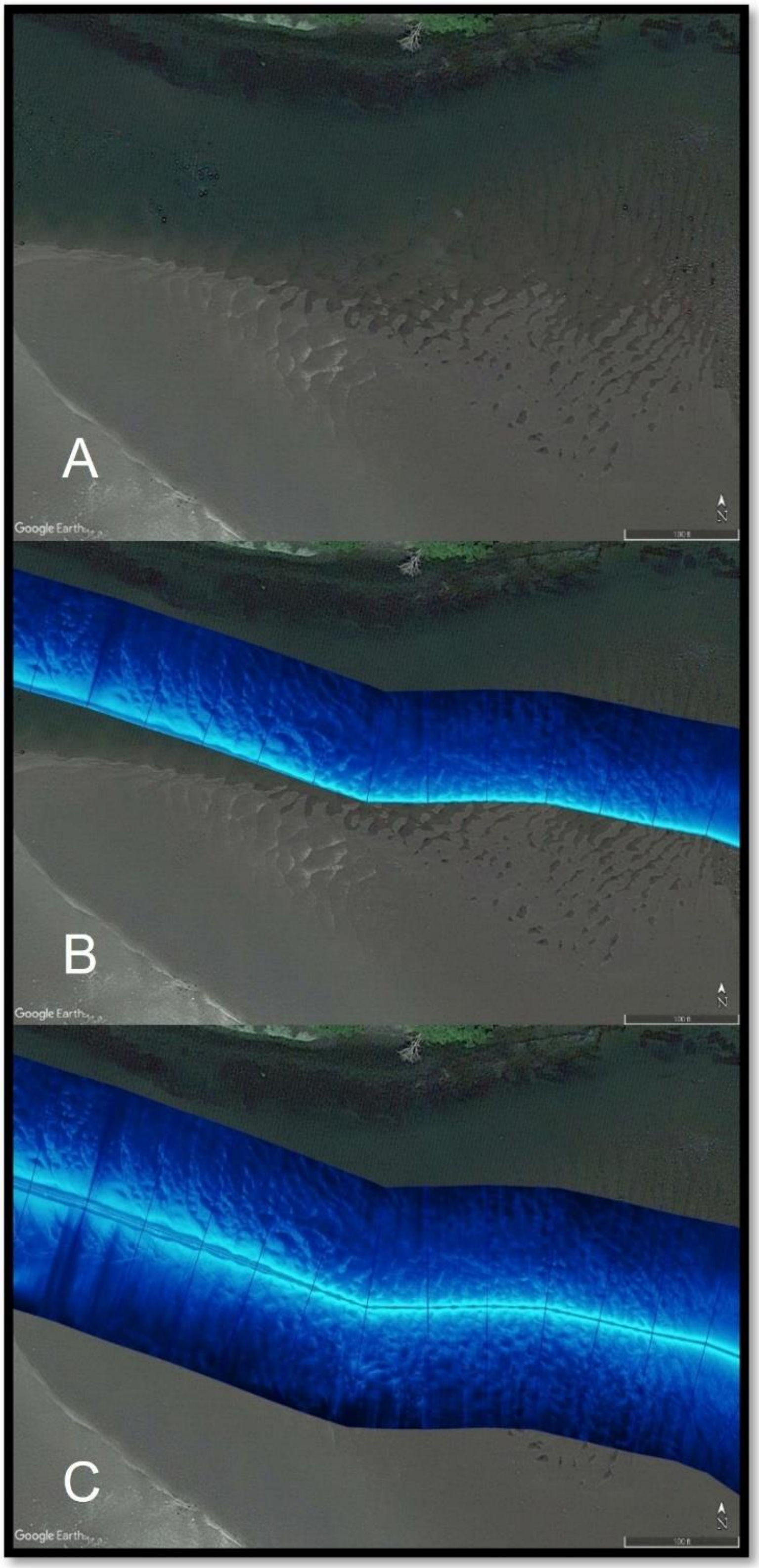

Figure 7. Sand substrate viewed through aerial imagery (Google Earth) and sonar images from the Salmon River estuary, Oregon.

Gravel

The images below show three different views of the same location on the Alsea River. Figure 8 is an on-the-ground visual verification of the gravel river bottom substrate. Figure 9 is a Google Earth satellite photo representing the area surveyed. Figure 10 is the sonar recording applied over the top of the Google Earth satellite photo. The sonar recording highlights the gravel substrate that makes up the entirety of this section.

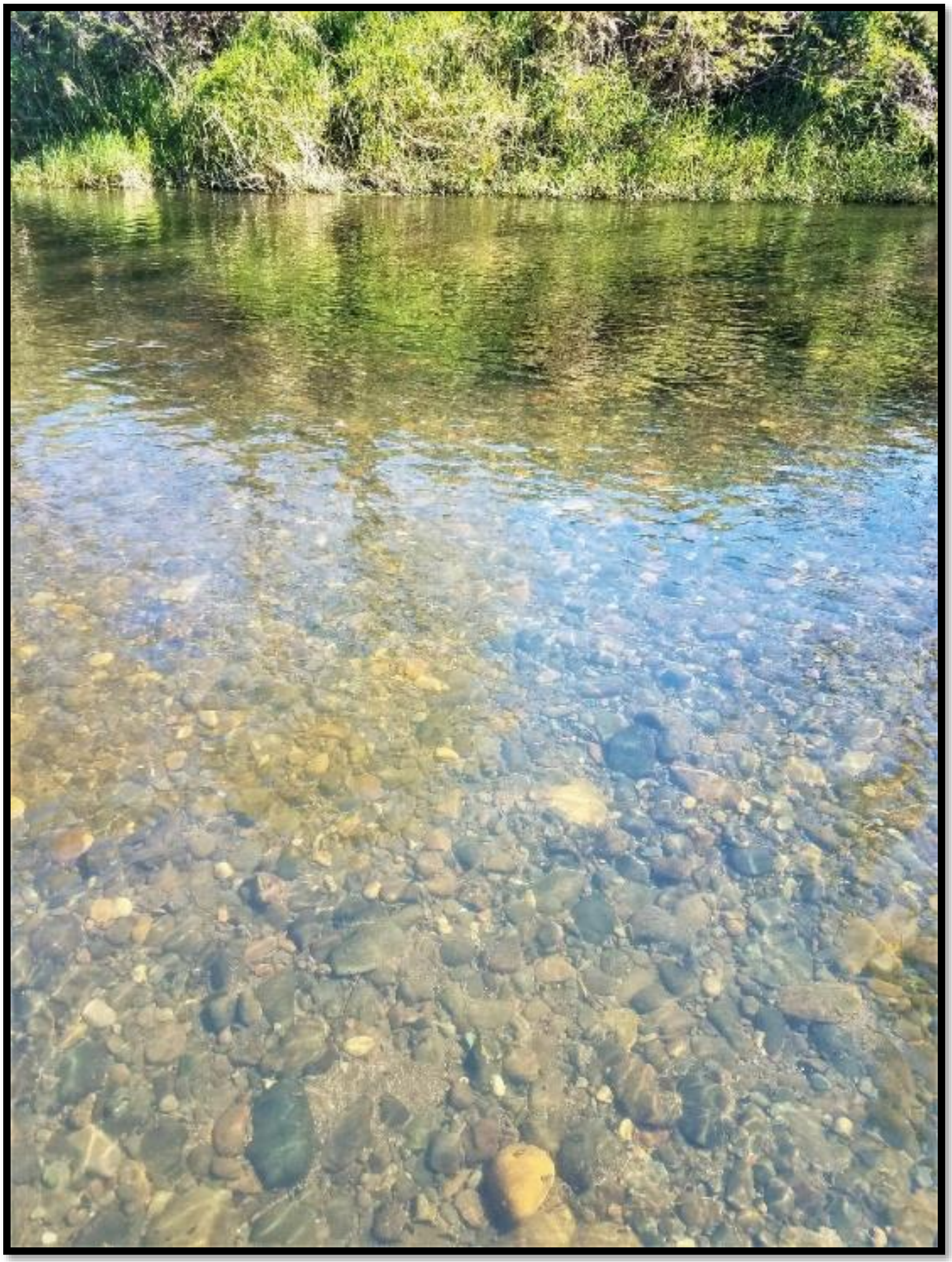

Figure 8. Site-level view of gravel substrate on Alsea River, Oregon. Photo Credit: Eric Bailey

Figure 9. Aerial overview of the surveyed area. Alsea River, Oregon. Google Earth image.

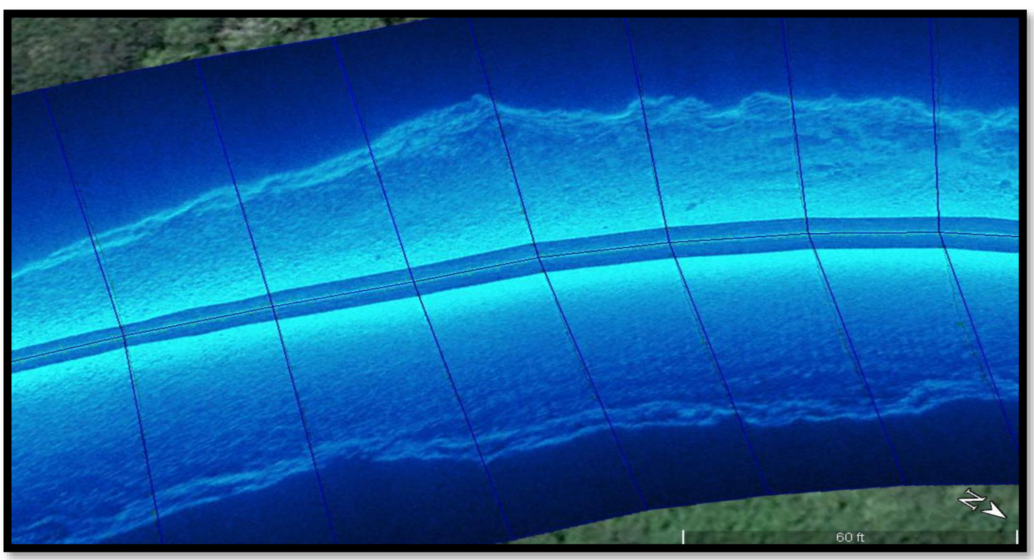

Figure 10. Sonar imagery of surveyed area on Alsea River, Oregon. Google Earth background image.

When reading the sonar images, the gravel substrate presents a more granular texture than silt or sand. The tone of gravel will generally read as homogenous and uniform in appearance in contrast to sand's smooth wave-like patterning. However, gravel will take the shape of the river's edge as it rises and falls throughout the year, creating a rolling step-like pattern at the bank margins highlighted in Figure 11.

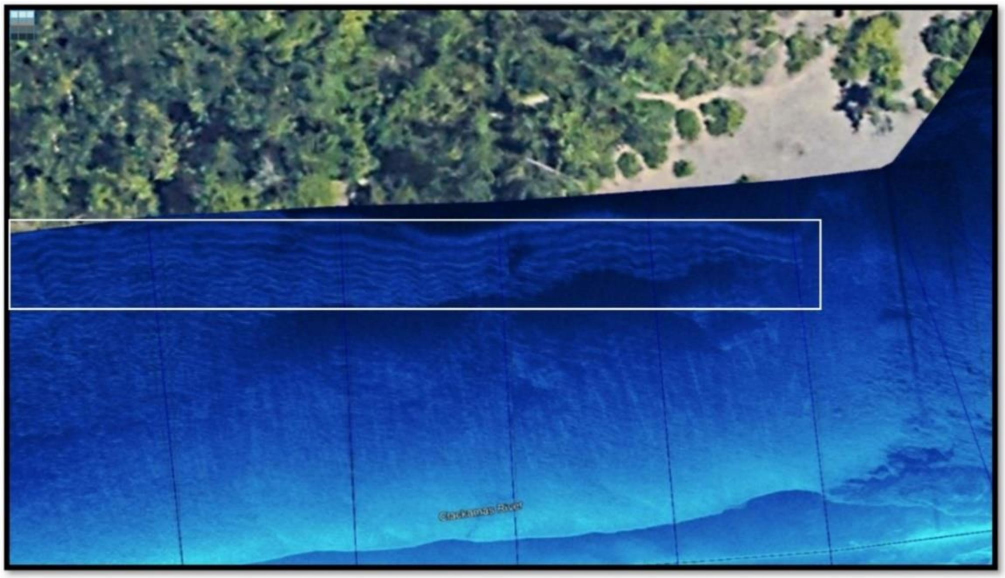

Figure 11. Gravel substrate along bank margin, Willamette River, Oregon. Google Earth background image.

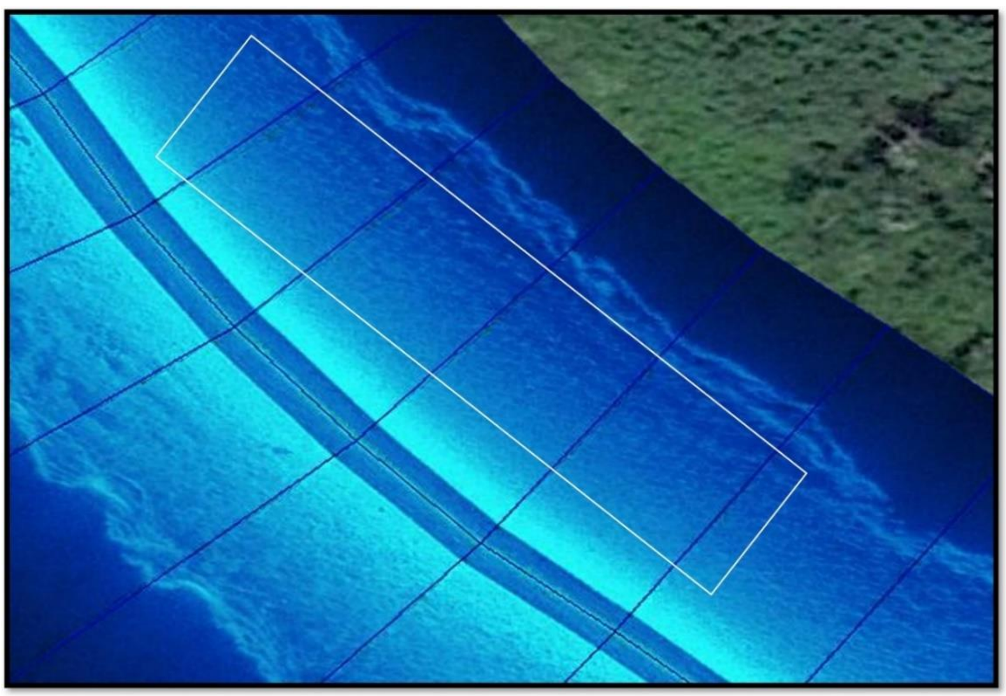

Figure 12. Gravel substrate along inside bend of the river channel, Willamette River, Oregon. Google Earth background image.

Cobble

Cobble and gravel have a similar appearance when reading the sonar image. Often both substrates will be mixed. One visual clue to telling the two substrates apart is paying close attention to the sonar image's grain size. Gravel substrate has a finer appearance in its granular roughness. In comparison, cobble substrate is coarser in its texture. Figure 13 shows a section of the Clackamas River dominated by cobble substrate.

Figure 13. Cobble dominated section of the Clackamas River near the confluence with Eagle Creek, Oregon. Image credit: Erik Suring.

A large, exposed cobble bar on the edge of a fast water habitat unit type is shown in the figure above. In Figure 14, the right channel of the sonar recording has been applied over the Google Earth image revealing a texture that matches the texture of the exposed cobble bar. When both channels of the sonar recording are used (Figure 15), a consistent granular pattern emerges, verifying that this section of the riverbed is indeed dominated by cobble substrate. An on-the-ground ocular survey has also confirmed this.

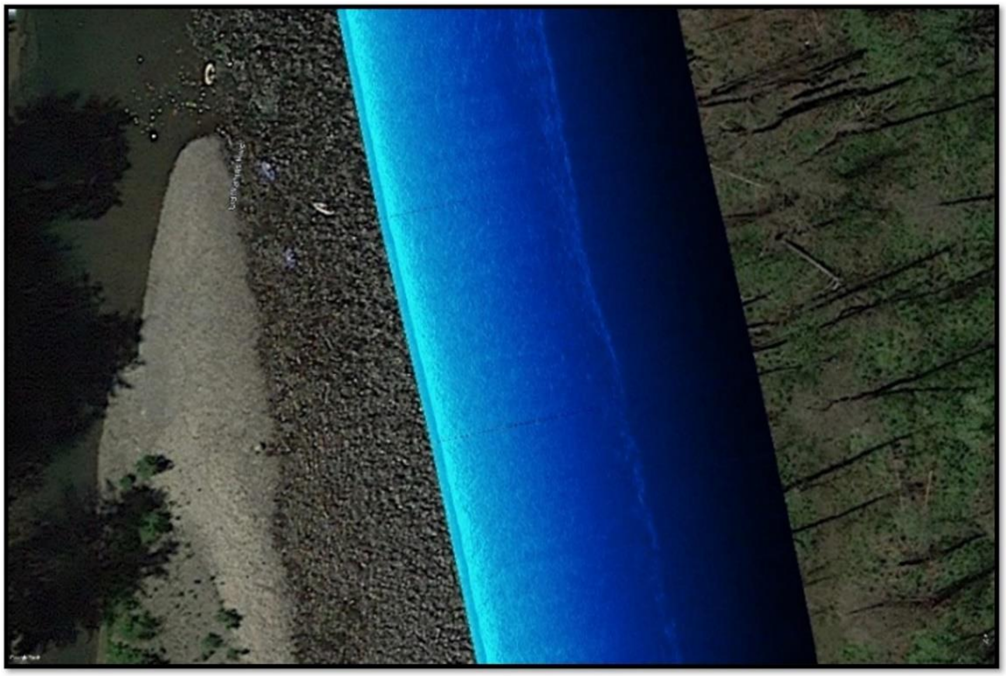

Figure 14. Cobble dominated section of the Clackamas River near the confluence with Eagle Creek, Oregon, with a right channel sonar overlay. Background image credit: Erik Suring.

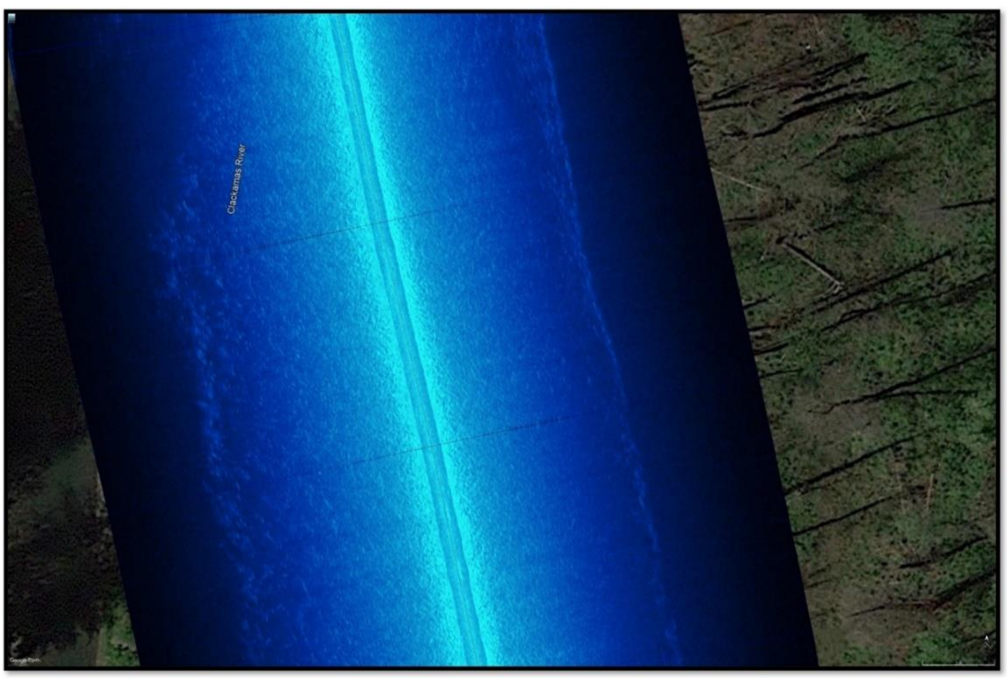

Figure 15. Cobble dominated section of the Clackamas River near the confluence with Eagle Creek, Oregon with sonar overlay. Background image credit: Erik Suring.

Figure 16 shows images taken on the Siletz River that illustrate gravel and cobble substrate mixing (A and B).

Figure 16. Images showing bedload mix of gravel and cobble substrate in Siletz River, Oregon.
Photo Credit: Eric Bailey

Figure 17 depicts sonar imagery where both gravel and cobble substrates are present in a section of the river. The white outlined areas show individual substrate classes that are primarily isolated from other substrate types. The red outlined area shows where gravel and cobble substrates are mixed evenly. In areas where substrate classes are mixed, the differences can be subtle, and often, an on-the-ground verification performed when the river is at its lowest can help define and quantify the substrates.

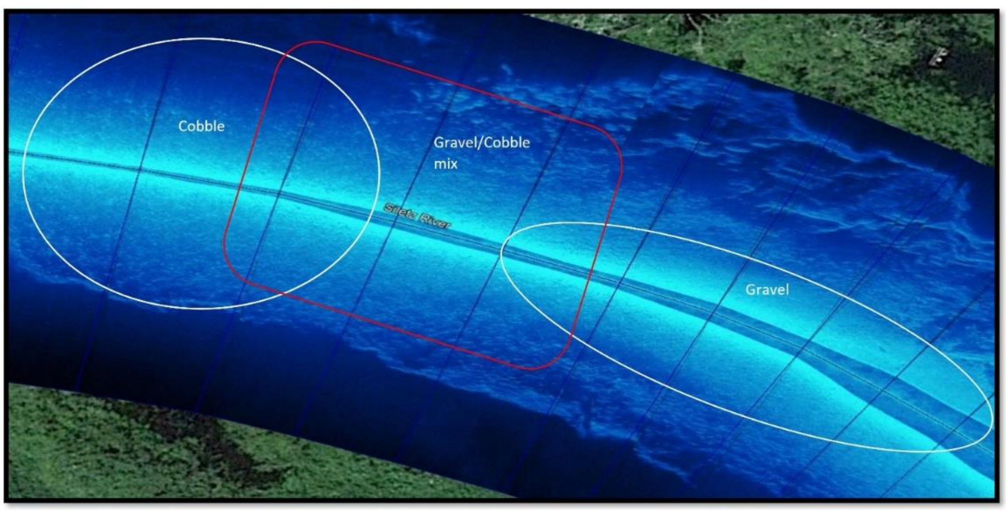

Figure 17. Sonar imagery on the Siletz River, Oregon showing bedload areas of gravel and cobble substrate. Google Earth background image.

Boulder

Boulders are the largest individual substrate and have a much more defined appearance on the sonar compared to finer substrates. Boulders are often easier substrates to identify when reading the sonar image due to their distinct textures and contrasting sonar shadows. Because the sonar beams cannot penetrate solid objects, when the beams strike an object such as a boulder, the sonar beam hits only the face of the boulder, leaving a dark cast shadow on the backside of the boulder (Figure 18). The length of this shadow can indicate the size of the boulder and the depth of the water. This shadow does represent lost data on the sonar image as any substrate directly in line with the shadow is not recorded. However, this can be adjusted for by on-the-ground verification.

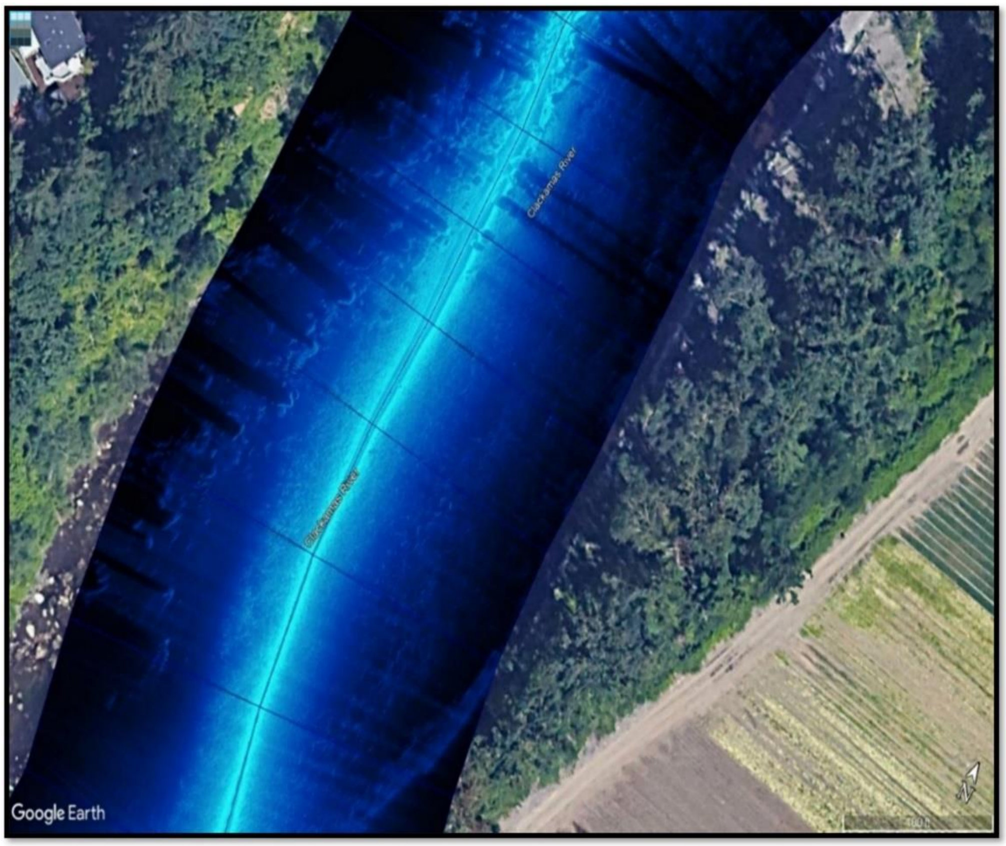

Figure 18. Sonar imagery and boulders on the Clackamas River, Oregon. Google Earth background image.

Google Earth imagery from Figure 19 shows a section of the Clackamas River bedload dominated by boulders.

Figure 19. Google Earth imagery showing exposed and submerged boulders from the Clackamas River, Oregon.

When the sonar imagery is overlayed on the section of Clackamas River depicted in Figure 19, the sonar beam detected boulders as well as the substrate behind the boulders indicating that the water was deep enough for the sonar to pass over the solid boulder and see the substrate up to the bank margins (Figure 20).

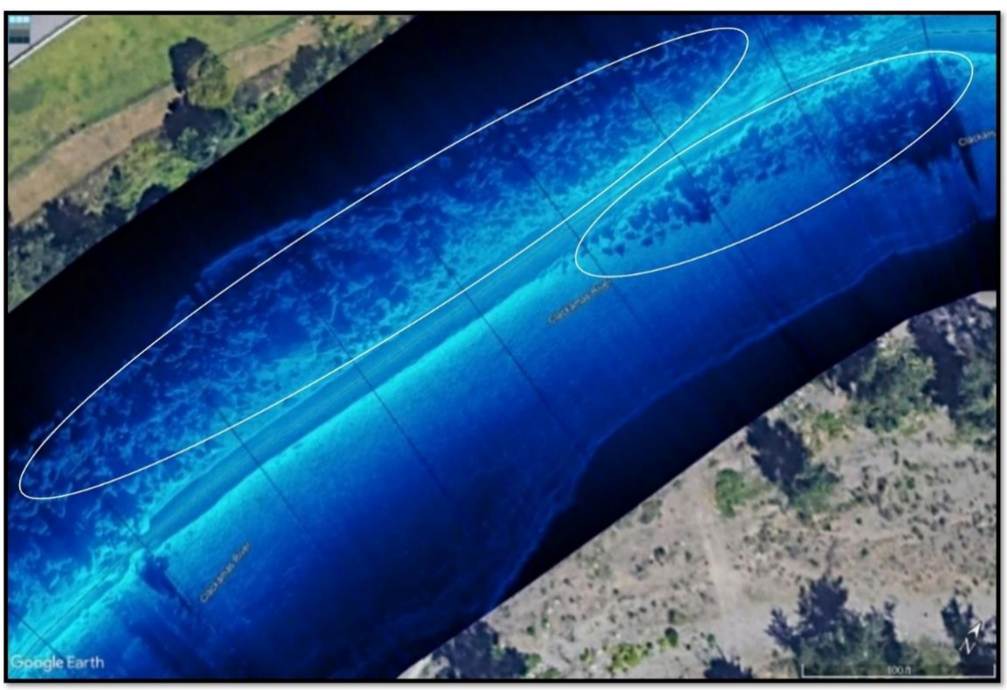

Figure 20. Sonar imagery from the Clackamas River, Oregon. Outlined areas dominated by boulders. Google Earth background imagery.

Bedrock

Bedrock is hard consolidated rock and has distinct patterns and textures that make it easily identifiable on the sonar. Due to the hard surface of bedrock, its amplitude is reflected in darker, more defined tones. Although bedrock can be partially covered with other substrates, it is easier to identify in many ways due to its defined patterning, tone, and texture. It can be easy to recognize when combined with aerial imagery that shows large outcropping of bedrock (Figure 21).

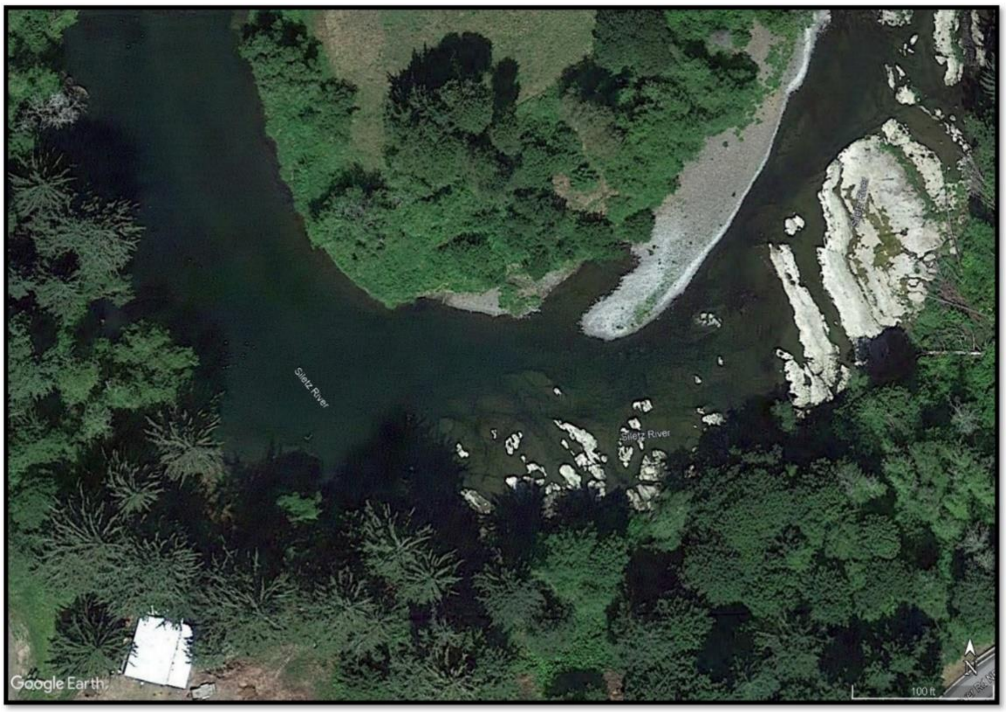

Figure 21. Google Earth imagery from the Siletz River, Oregon, showing exposed and submerged bedrock.

The Google Earth imagery from Figure 21 shows a large concentration of exposed bedrock protruding above the water's surface. When the sonar is applied in Figure 22, bedrock accounts for much more of the substrate than is visible by the naked eye from aerial imagery. Outlined areas highlight portions of the bedload comprised entirely of bedrock.

Figure 22. Sonar imagery from the Siletz River, Oregon, highlighting areas of bedrock substrate. Google Earth background imagery.

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