

Automated Sediment Characterization to Understand Long-Term Coastal Change in Response to the Elwha River Dam Removal

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Abstract

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Sediment characteristics – relative proportions of sediment fractions and the prevalence of wood or other organic debris – are a fundamental property of coastal systems, influencing storm response, habitat quality, and long-term shoreline evolution. Sediment characteristics and coastal morphology vary in time and space with sediment supply, wave activity, and other local dynamics. Despite their hypothesized importance, the co-evolution of sediment characteristics and coastal morphology remains poorly understood in mixed sediment environments due to challenges with data collection and analysis. The dataset used in this research is made up of 15,000 sediment images collected from 2009 to 2023 on the Elwha River delta and adjacent downdrift coastlines in Washington. This research focuses on the annual co-evolution of sediment characteristics and coastal morphology following a major flux of sediment to the system after the undamming of the Elwha River. SegFormer models were integrated into an automated image segmentation workflow and trained to identify and quantify the relative proportions of sediment fractions and organic debris across this long-term dataset. The results from these models show clear spatial and temporal variability in sediment composition across the Elwha River delta following dam removal, with shifts in the relative proportions of sand, gravel, and cobble over time. Following dam removal, sand increased near the river mouth and gradually propagated alongshore as the delta transitioned

from a coarse-dominated to a sand-dominated shoreline. Sand accumulated on the upper beach of downdrift coastlines, suggesting that cross-shore processes were also important for sediment redistribution. A strong link between sediment delivery and coastal response was identified, demonstrating how machine learning-based image segmentation can be used to monitor mixed-sediment coastal change.

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Chapter 1

INTRODUCTION

Sediment characteristics, including the proportions of sand, gravel, cobble, and organic debris, are a fundamental property of coastal systems. The distribution of these fractions across the beach can provide insight into sediment distribution and coastal change. Sediment fractions influence storm response, post-storm recovery, and long-term shoreline evolution [30]. They also affect habitat suitability and the effectiveness of restoration efforts, linking coastal morphology with ecological outcomes. Both sediment fractions and coastal morphology vary in time and space in response to sediment supply, wave climate, and tidal dynamics [14]. Changes in sediment amount and grain size influence shoreline position and patterns of erosion and accretion over time [31].

1.1 Mixed Sediment Beaches and Co-Evolution

Coastal environments are rarely composed of a single grain size and instead include a range of sediment sizes, from predominantly sandy beaches to mixed sediment systems containing sand, gravel, cobble, and organic material. Global-scale assessments of beach morphology and shoreline characteristics show that while sandy beaches account for approximately 31% of the world's ice-free shoreline, coastal environments show strong spatial variability in non-sandy shoreline types such as sea cliffs, tidal flats, river deltas, and other sedimentary environments [19]. In these systems, sediment transport processes are strongly size-dependent which leads to sorting, selective transport, and spatial variability in grain size distributions (Figure 1.1). Coarser materials like gravel and cobbles are harder to transport and allow water to drain more quickly, while finer sands and silts are more easily stirred up by waves and currents and stay suspended in the water column for longer. Coarse sediments are therefore more likely to

stay in place and form armored surfaces that can slow further erosion [26]. The winnowing of fine sediments and the progressive armoring of the beach surface create strong feedback between sediment supply and coastal morphology [12]. Mixed-sediment beaches therefore behave differently from both sand and gravel beaches because fine and coarse sediments respond differently to waves and currents [20].

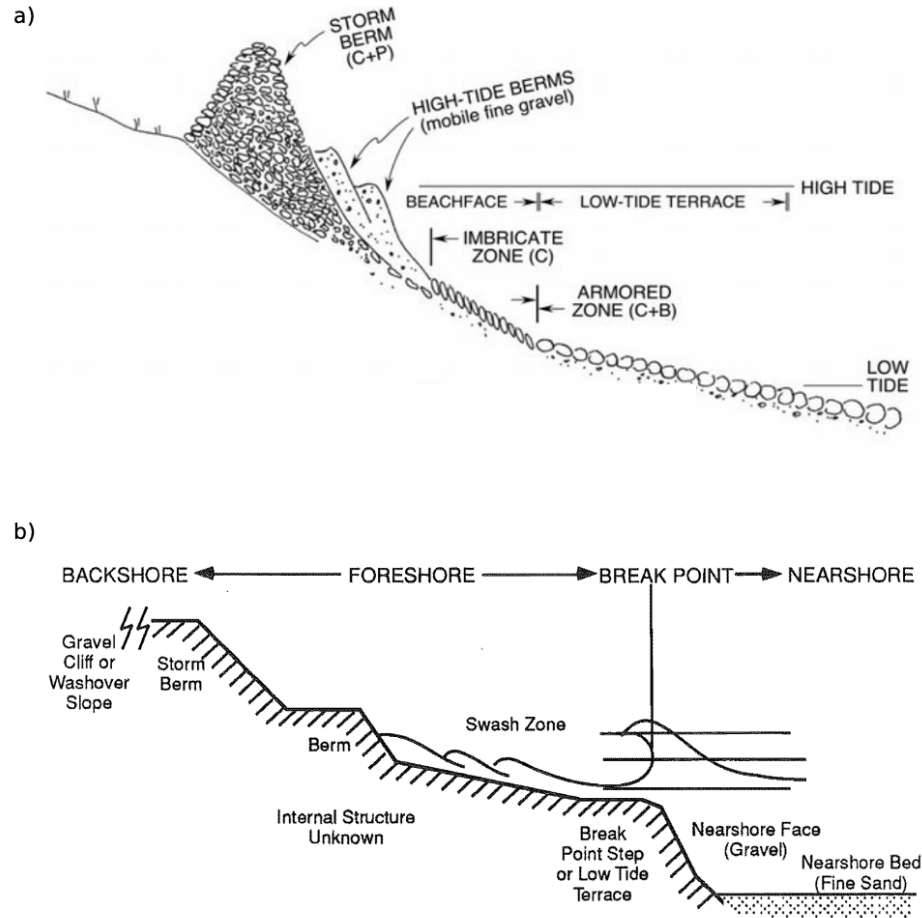


Figure 1.1: Examples of mixed-sediment beach profiles showing cross-shore zonation. Figure (a) illustrates the accumulation of finer sediment burying coarser material, while Figure (b) highlights the geomorphic zones of mixed-sediment beaches. Reproduced from [16, 18]

These processes reflect the coupled evolution of sediment composition and beach mor-

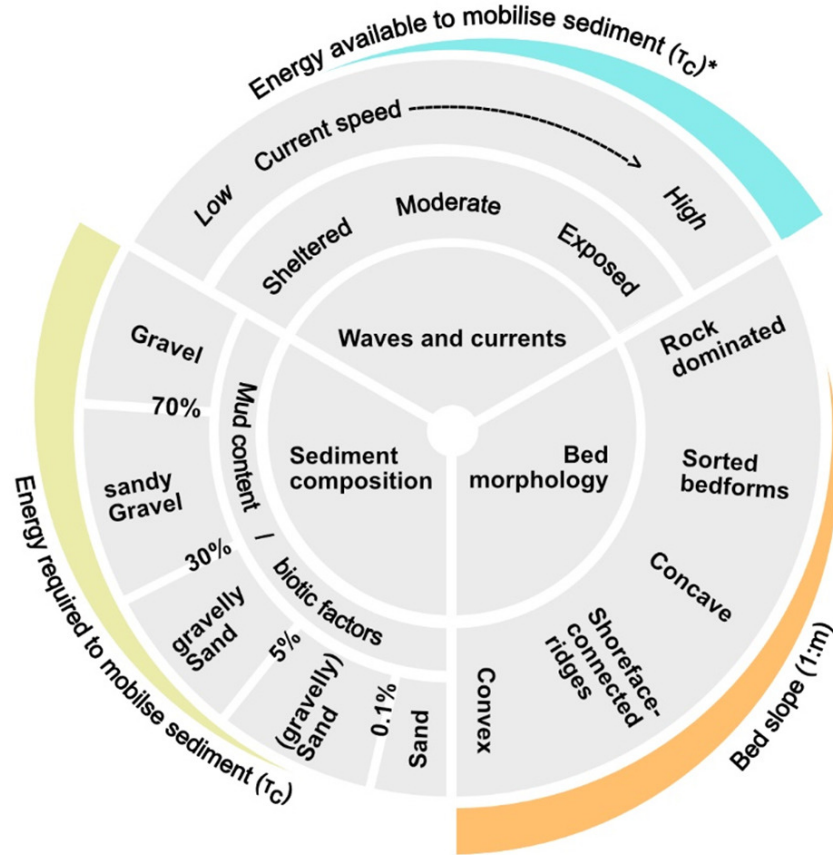
phology, often referred to as morpho-sedimentary dynamics [8]. In these systems, sediment characteristics and coastal morphology evolve together through transport and deposition [8]. For example, when sediment supply decreases, the beach surface tends to become coarser, increasing resistance to wave action and changing how waves break nearshore. When sediment supply increases, finer material can bury coarser layers, adjust beach slope, and shift nearshore flow patterns by causing morphological changes such as the formation of bars and berms [12]. Sediment grain size distributions not only indicate coastal change, but also help shape how the system evolves [23, 12].

Mixed sediment beaches are challenging for researchers to understand and predict because they contain a wide range of grain sizes. Different sediment sizes are transported at different rates which creates complex spatial and temporal sorting patterns [8, 20]. In contrast, sandy beaches can often be approximated by using a single representative grain size. Traditional sediment transport models struggle in mixed sediment environments because they must represent the transport and sorting of multiple sediment sizes simultaneously. Many existing models were developed for sandy or gravel beaches and are more difficult to apply to mixed sediment beaches [20]. This makes it difficult to predict how sediment composition and beach morphology will respond to changes in sediment supply [23].

1.2 The Importance of Sediment Fractions

Although detailed grain-size distributions can provide important sediment information, sediment fractions such as sand, gravel, cobble, and organic material still capture the dominant physical and ecological characteristics of coastal systems. This approach assumes that sediment fractions respond differently to waves and currents. Finer and coarser sediments require different amounts of energy to become mobile, resulting in different transport and deposition patterns (Figure 1.2) [26]. As a result, sediment fractions provide a reliable representation of how sediment is transported by waves and currents, how wave energy dissipates across the beach, and how shorelines adjust to changing conditions. Grain-size distributions also influence beach slope and cross-shore profile evolution, and together these characteristics drive

patterns of shoreline erosion and accretion, influencing overall shoreline stability [29]. Representing sediment as discrete fractions provides a simpler way to characterize mixed-sediment systems while preserving many of the factors that influence coastal change.



*Presence of currents can add/detract energy available depending on current direction

Figure 1.2: Conceptual model showing how sediment composition, waves, currents, and beach morphology influence sediment transport and coastal evolution. Reproduced from [26]

From an ecological perspective, sediment composition shapes habitat suitability for inter-tidal and nearshore species, and these differences can be captured by broad sediment fractions such as sand, gravel, and cobble rather than detailed grain-size distributions. Grain-size controls pore space, permeability, and seabed stability. In mixed-sediment environments, these

properties can shift over relatively short distances, which can create a non-uniform seafloor made up of different habitat types. This is important because different grain fractions tend to support different benthic communities [29]. As sediment fractions shift along the shoreline, the associated habitats shift with them [27]. For example, areas with finer sediments can support shellfish populations, while coarser substrates are a much less suitable shellfish habitat [14].

Overall, sediment composition plays a fundamental role for nearshore ecosystem structure and biodiversity by shaping habitat composition and influencing how coastal environments respond to environmental change. Recognizing these links between sediment composition, coastal processes, and ecosystem function is essential for effective management and conservation of shoreline environments [14].

1.3 Existing Approaches for Measuring Sediment Composition

A major goal in coastal geomorphology is to develop reliable ways to track how sediment characteristics change through space and time. In particular, understanding how sediment grain size and coastal landforms evolve together aids in interpreting coastal processes and predicting shoreline response [6]. Traditionally, collecting sediment data over large spatial and temporal scales has been time-consuming, relying on field sampling and laboratory analysis. With recent advances in remote sensing and image analysis, automated digital approaches have emerged for characterizing sediments, which are generally grouped into statistical, deterministic (object-based), and machine learning methods.

Grain-size distributions and sediment fractions are closely related but describe different aspects of sediment composition. Grain-size analyses measure the amount of sediment within different grain-size classes, whereas sediment fractions measure the proportion of the beach surface that is made up of sand, gravel, cobble, and organic material. These approaches provide complementary information but answer different questions. Because this study focuses on how sediment composition changes across the beach surface through time, a segmentation approach was used to classify sediment fractions directly from imagery.

1.3.1 *Statistical Methods*

Statistical approaches estimate sediment properties from image features such as intensity and texture. Methods like optical granulometry, wavelet-based analyses, and autocorrelation-based tools such as pyDGS and CobbleCam relate these image characteristics to grain size through mathematical relationships, once the imagery has been referenced and calibrated against field or laboratory measurements [28, 4]. These approaches treat the image as a textured surface rather than resolving individual grains, and infer grain-size statistics from patterns in brightness and texture. While they can be effective and relatively efficient, they require careful calibration and are often less reliable in mixed or poorly sorted sediments, where variability in grain size and composition complicates the link between image texture and physical sediment properties.

1.3.2 *Deterministic Methods*

Deterministic, or object-based, methods such as photosieving, Automated Grain Sizing (AGS), and object-based image analysis (OBIA) segment images into discrete particles to extract geometric properties such as grain size and shape [15, 6]. AGS research demonstrated that digital image processing techniques could provide grain-size estimates comparable to traditional field measurements [15]. However, these techniques depend on being able to clearly identify individual grain boundaries which makes them perform best in coarse-grained environments where grains are larger than a single pixel. The accuracy of these methods can also be inconsistent due to overlapping grains, shadows, and organic material. As a result, although deterministic methods can provide detailed grain-size information, they are limited by image resolution and the complexity of sediment characteristics.

1.3.3 *Emerging Machine Learning Methods*

Recent advances in machine learning have enabled new approaches to characterizing sediments from imagery. Deep learning models can learn relevant features directly from raw

images without the need for explicit feature engineering. This allows them to capture complex spatial variability in sediment composition. Models such as SediNet [5] and other deep learning architectures have demonstrated improved accuracy and generalizability across a range of environments, particularly in mixed-sediment systems. Existing machine-learning approaches have focused on estimating grain-size distributions or sediment facies from imagery [11]. Some methods can also predict sieve data directly from image features [21]. The semantic segmentation used in this study classifies sediment fractions rather than grain-size distributions. This makes it possible to track changes in the proportions of sand, gravel, cobble, and organic material over time. However, these approaches depend on large labeled datasets and require careful validation to ensure transferability across different field conditions [6]. Coastal systems with strong spatial and temporal gradients are therefore well suited for model development because they provide the range of conditions needed for reliable model training and evaluation.

1.4 Dam removal and delta evolution on the Elwha River, WA

River dams trap sediment that would otherwise naturally flow downstream to river deltas. They therefore fundamentally disrupt the delivery of this sediment to coastal systems. This disruption affects deltas worldwide by altering sediment budgets and accelerating coastal erosion. One example, The Aswan High Dam on the Nile River delta in Egypt, led to reduced sediment delivery, which resulted in shoreline erosion and reorientation along with the coarsening of nearshore sediments [13]. Spain’s Ebro delta shows similar patterns: upstream reservoirs reduced the delta’s sediment supply, accelerating coastal erosion and shifting the system from river-wave dominated to purely wave-dominated [17].

The Elwha River on Washington’s Olympic Peninsula also experienced river damming and the disruption of downstream shorelines. Nearly a century ago, two dams were constructed along the Elwha River: the downstream Elwha Dam (built in 1913) and the upstream Glines Canyon Dam (built in 1927). Over that century, these two dams trapped roughly 21 million m³ of sediment, effectively eliminating sediment transport from the upper watershed

to the river mouth and significantly changing the Elwha River delta as well as neighboring shorelines (Figure 1.3) [29, 14]. The Elwha watershed drains about 831 km² of the Olympic Mountains. By 1995 roughly 13.5 million m³ of sediment had accumulated in reservoirs created by the dams, roughly half comprising of finer sediment (silt and clay) and the other half of coarser sediment (sand, gravel, cobble) [29]. Before the dams were removed, the coast eroded at about 0.6 m yr⁻¹. Waves gradually winnowed away finer sediments, which left a coarse cobble beach that changed nearshore processes and reduced habitats for many species. These sediment-starved conditions persisted for nearly a century.

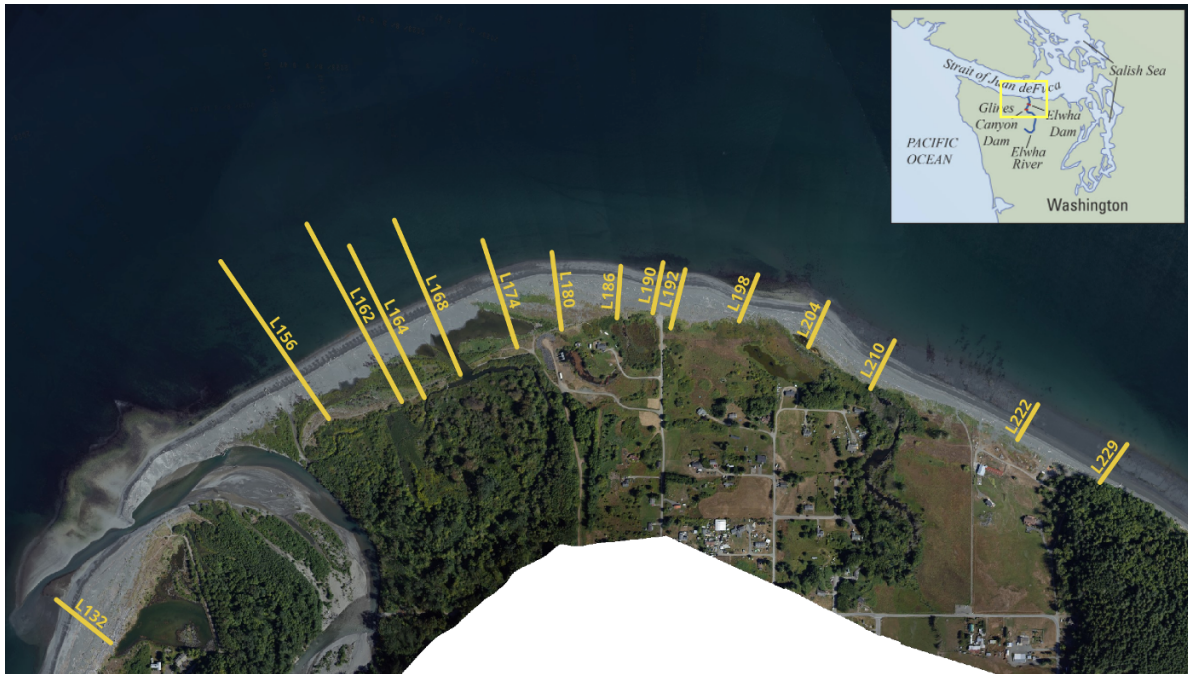


Figure 1.3: Orthophoto (2023 Plane Cam image [24]) of the Elwha River delta showing the shoreline east of the river mouth. Prior to dam removal this section of shoreline was chronically erosive and composed primarily of coarse sediments. Also depicted are cross shore transects [22] used for shoreline and sediment analysis in this study

The Elwha River flows into the Strait of Juan de Fuca, where coastal processes are

shaped by waves and tides. Although wave energy in the Strait is lower than along the coast, the waves primarily approach from the northwest as the swell enters from the ocean [14]. These waves transport sediment east along the shoreline and shape beach morphology and shoreline changes over time. The Strait also experiences wave energy variability, and the higher energy episodic storms can redistribute substantial amounts of sediment across the delta [29]. These wave and tide processes strongly influence sediment redistribution throughout the Elwha delta and help shape patterns of erosion, accretion, and sediment sorting.

The removal of the Elwha and Glines Canyon dams between 2011 and 2014 represents one of the world’s largest sediment restoration projects, releasing an estimated 18 million tonnes of stored sediment into the river and ultimately being transported to the delta [30, 14]. Researchers conducted semi-annual topographic and bathymetric (“topo-bathy”) surveys from pre- to post-dam-removal periods to track the dramatic changes that followed the removal of the dams (Figure 1.5). These surveys captured how the Elwha River delta evolved in both elevation (topography) and shoreline position over time. Planview maps of the delta (Figure 1.4) illustrate these changes in shoreline position and sediment redistribution during this period.



Figure 1.4: Planview evolution of the Elwha River delta from DEM-derived surfaces showing pre-, during-, and post-dam removal conditions. Warm colors indicate higher elevations. Reproduced from [25]

In the years after the dam removals, the Elwha River delta prograded by hundreds of meters as the sediment plume dispersed along the coast [14]. Before dam removal, the Elwha delta exhibited alongshore variability, with steeper beaches west of the river mouth and a more cobble-dominated low-tide terrace to the east. This massive sediment influx transformed the shoreline and made the Elwha a valuable natural experiment for linking sediment supply and coastal response (Figure 1.5).

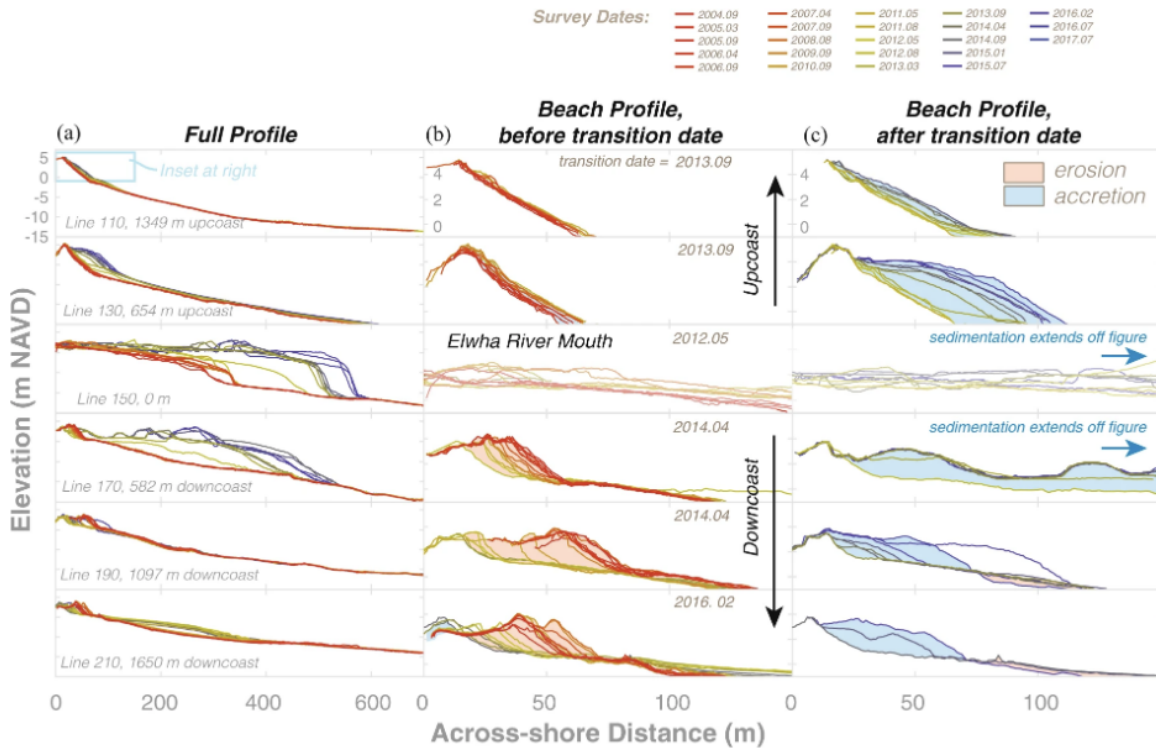


Figure 1.5: Six topobathymetric profiles of the Elwha River delta, spanning from upcoast to downcoast of the river mouth, where line colors indicate survey dates spanning 2004 to 2017. Beach profiles are shown for years prior and following a local transition from erosive to accretive conditions. Reproduced from [30]

1.5 Thesis Motivation and Research Questions

While large-scale geomorphic responses to dam removal and other coastal perturbations, such as shoreline progradation and erosion reversal, are well documented, there are limited studies that examine how sediment characteristics evolve alongside these changes. This gap is largely due to the lack of consistent, long-term observations of sediment composition. This thesis investigates the co-evolution of sediment characteristics and coastal morphology at the Elwha River delta from 2009–2023 by applying machine-learning image classification methods to examine spatial and temporal patterns in sediment composition and relate these changes to observed shoreline evolution following dam removal. This study addresses the following research questions:

- How have sediment fractions (sand, gravel, cobble, and organic debris) evolved spatially and temporally across the delta?
- How are these changes in sediment composition related to spatial and temporal patterns in beach morphology?

Given the limitations of statistical and deterministic methods in mixed-sediment environments, this study uses a machine learning-based image segmentation approach. In this project, SegmentationGym framework [7], a SegFormer model, is implemented to classify sediment imagery into sand, gravel, cobble, and organic debris. This segmentation is done directly from pixel values, without explicitly identifying individual grains. Applied to annual sediment imagery collected between 2011 and 2023 at the Elwha River delta [22], the model provides a consistent and reproducible way to track spatial and temporal changes in sediment characteristics and to examine how sediment composition and coastal morphology co-evolve in response to large sediment pulses from dam removal.

Chapter 2

METHODS AND DATA

2.1 Dataset

2.1.1 Dataset Overview

This thesis analyzes long-term imagery and topo-bathymetric survey data collected at the Elwha River delta. The relevant dataset spans from 2009 prior to dam removal, through 2023 almost a decade after the removal of the Elwha and Glines Canyon dams. This time frame shows how the shoreline changed before, during, and after sediment restoration. Sediment imagery was used for machine learning image segmentation for characterizing sediment, while topo-bathymetric data [25] provided context for coastal morphology. Together, these datasets allow for analysis of how sediment composition and geomorphic change vary across space and time along the Elwha River delta.

The dataset includes approximately 15,000 sediment photographs collected at cross-shore transects across the Elwha River delta from two survey types: approximately 6,700 images from monthly high-frequency grain-size monitoring across four transects, and approximately 7,300 images from annual summer surveys that cover complete transect profiles across more than 20 transects (Figure 1.3) [22]. These images span three distinct geomorphic environments of the Elwha coastal system (Figure 2.1): the steep, cusped beach west of the river mouth (Figure 2.1a), the active river mouth zone (Figure 2.1b), and the cobble-dominated low-tide terrace east of the mouth (Figure 2.1c) [29], capturing alongshore variation in sediment supply, wave energy, and beach morphology across the shoreline.

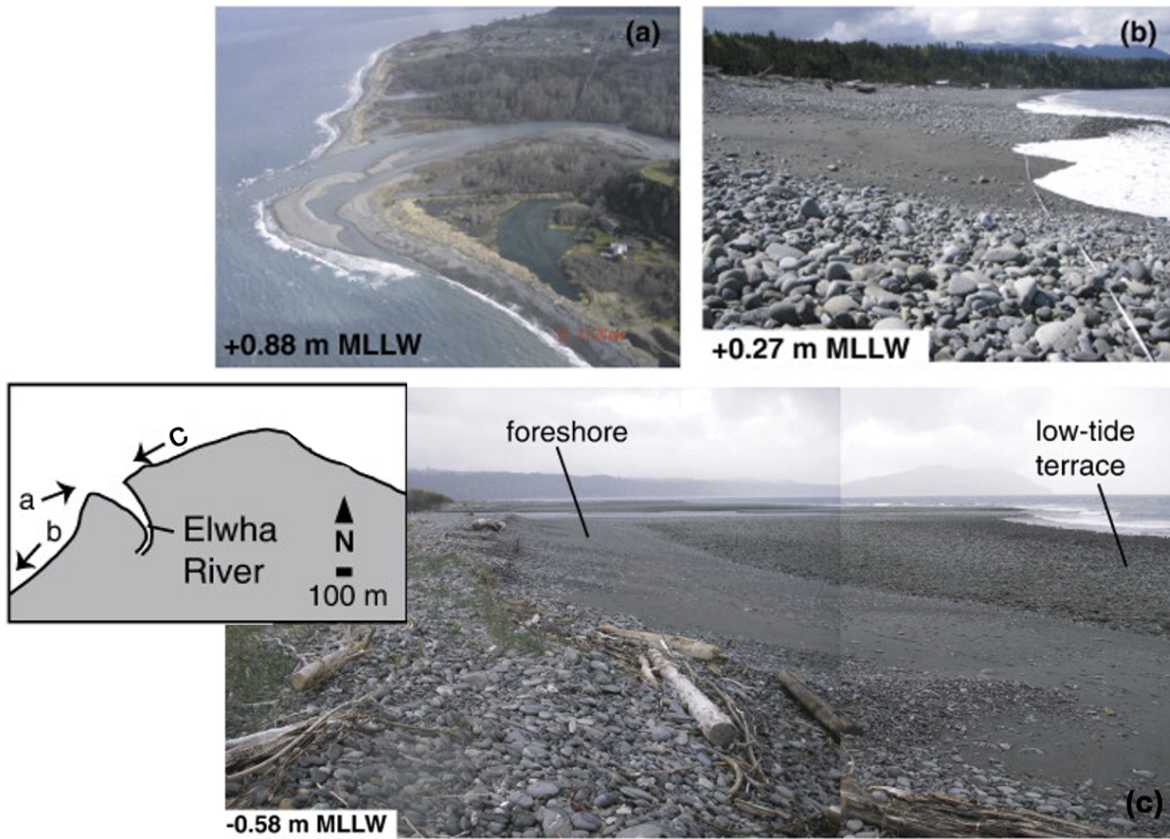


Figure 2.1: Defined geomorphic zones of the Elwha River delta, including the west beach, river mouth, and east low-tide terrace. Reproduced from [29]

2.1.2 Sediment Image Dataset

This study focuses on the annual survey dataset because it provides broader spatial coverage and tracks sediment characteristics both alongshore and cross-shore at an annual scale, reflecting how the system evolves in response to sediment flux.

These close-up photographs of the beach surface taken from roughly waist height capture a detailed view of the shoreline sediment (Figure 2.2). Each image typically shows a mix of sediment types- sand, gravel, cobble, and organic debris such as wood or seaweed- and represents a small patch (approx. $0.5\text{--}1\text{ m}^2$) of the beach along a transect. A scale bar is included in every image. The annual survey images were primarily collected during summer

surveys from 2011 to 2023, with additional winter surveys carried out during the dam removal period from 2011 to 2016, when the highest volume of dam-released sediment was transported to the coast.



Figure 2.2: Example shoreline image from the Elwha River delta showing mixed sediment. Reproduced from [22]

The images were collected using a standardized field approach to maintain consistency across the dataset [29]. Camera height and angles were kept as consistent as possible and the scale bar allows grain-size to be compared across time and space. However, there is some variation in the scale bars and cameras over the entire survey period.

The images also naturally vary in both appearance and complexity. Some show relatively uniform sediment patches consisting of a single grain fraction, while others contain multiple sediment fractions. Some images also include organic material such as kelp, driftwood, algae, or barnacles on cobbles. At lower elevations, some of the images also contained standing water on the sediment surface. This variability makes automated segmentation useful because it allows sediment fractions to be characterized across many different shoreline conditions.

However, the presence of mixed sediments, organic material, and standing water can make classification more difficult.

2.1.3 Topographic, Bathymetric, and Morphological Data

This research also uses topo-bathymetric survey data collected across the Elwha River delta to understand changes in coastal morphology, which is divided into subaerial (above-water) and subtidal (below-water) zones. These surveys include both beach topography and nearshore bathymetry, capturing how the system responds to changes in sediment supply across intertidal and nearshore areas of the delta. Topographic and bathymetric measurements were collected using survey-grade global navigation satellite system (GNSS) receivers, and together form a representative elevation dataset across both the beach and nearshore regions.

These point measurements were collected as part of U.S. Geological Survey (USGS) and Washington Department of Ecology topo-bathymetric surveys of the Elwha River delta [25]. This survey data was used to generate digital elevation models (DEMs), which provide continuous surfaces of coastal morphology. The topo-bathymetric DEMs combine subaerial and subtidal elevations into a single representation of the coastal surface which allows changes in shoreline position, beach slope, and patterns of erosion and deposition to be examined over time. In this sediment composition research, the DEMs are used primarily as a supporting dataset by providing a broader morphological context and serving as a reference for elevation and volumetric change of the shoreline over time [25, 14].

In addition to the survey and elevation data, aerial imagery collected using plane-mounted cameras [24] was used to support the visualization of shoreline change across the delta. This dataset was used as a base layer in a web application and provided a visual reference for tracking how sediment characteristics and shoreline position change through time. While not used directly in the quantitative analysis, the plane-cam imagery provides a more extensive spatial context for the DEM and sediment imagery [24].

2.2 *Machine Learning Model Development*

The Doodleverse is a collection of open-source Python packages developed for image segmentation in geoscience applications using machine learning. This framework uses a “human-in-the-loop” approach, where users provide annotations that are used to guide and improve automated image classification [9]. This makes it easier to label complex imagery while maintaining control over the results, which is especially useful in natural environments where surface textures vary and class boundaries may be unclear.

In this study, two packages in the Doodleverse collection were used: Dash Doodler [10] and SegmentationGym [7]. Dash Doodler was used to generate labeled training data through interactive image annotation, while SegmentationGym was used to train and apply deep learning segmentation models. These packages provided a streamlined workflow for this study by linking data labeling, model training, and predictive classification for sediment image analysis of the Elwha River delta [1].

2.2.1 *Training and Validation Data*

Dash Doodler is an interactive annotation tool within the Doodleverse framework used to create labeled data for semantic segmentation models such as SegmentationGym [7]. Instead of requiring fully manual digitization or relying on fully automated labeling, it allows users to add simple annotations (“doodles”) that are then used to perform automated labeling on the rest of the image.

In this study, Dash Doodler was used to label all images for both training and evaluation. A subset of 256 images were labeled and randomly divided into training and validation subsets using a 60%40% split. These images included both typical conditions and more challenging cases, such as mixed sediment textures and images with organic material. The training subset was used during model training, while the quasi-independent validation subset was withheld from model training and used to evaluate model performance.

An additional set of 30 images was labeled as a fully independent test set, which was

chosen to represent the range of conditions across the full dataset. This set included different sediment types as well as variation in scale bars, organic material, shadows, barnacles, and standing water. The test set was labeled to capture the dataset’s overall variability. Together, these datasets provided a thorough representation of conditions across the study area and supported reliable model training and evaluation.

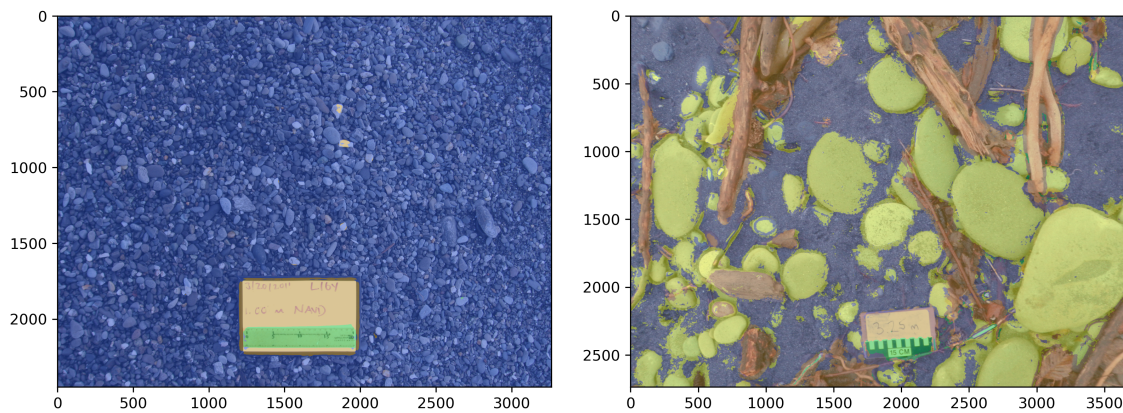


Figure 2.3: Example test set labeled images created using DashDoodler. Colored overlays show the ground-truth classes used for model training and evaluation, including sand, gravel, cobble, organic material, scale bars, and other features.

2.2.2 Segmentation Model Architecture

Sediment classification in this study was performed using the SegmentationGym framework, a deep learning system designed for semantic segmentation of scientific imagery and adapted for earth science applications [7]. It provides an end-to-end, reproducible workflow for training and applying semantic segmentation models to classify sediment types from beach imagery.

The framework uses a SegFormer encoder-decoder architecture (Figure 2.4), where each pixel is assigned to a specific class. The encoder extracts image features using a hierarchical Transformer structure that progressively reduces spatial resolution while preserving important information. As the network depth increases, the model captures increasingly complex

image features, allowing it to identify both fine-grained sediment textures and broader spatial sediment patterns. The decoder then combines features from multiple scales to produce pixel-level predictions, which are converted into pixel-wise class probabilities using a softmax function. Together, this architecture allows the model to resolve both fine-scale detail (e.g., individual grains) and broader spatial patterns (e.g., sediment distribution across the beach).

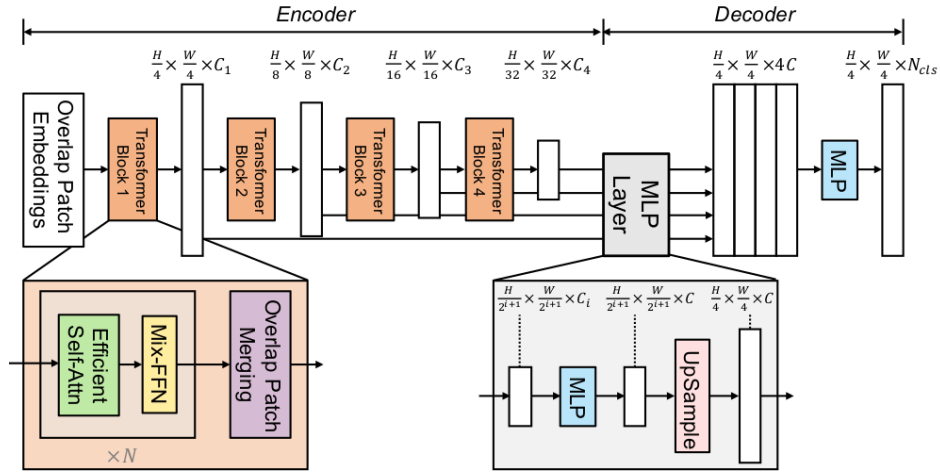


Figure 2.4: The SegFormer architecture used in SegmentationGym. Reproduced from [2]

The model is trained on a subset of labeled images using supervised learning and is optimized through backpropagation by comparing the model predictions to manually defined ground truth labels using a loss function [7]. To improve performance and reduce overfitting, the model also applies data augmentation during training, including image rotations, zooming, and horizontal and vertical flips. These augmentations help improve the models performance across the full dataset by adding variation within an image while keeping the sediment content unchanged.

Capturing both fine detail and broader spatial patterns is especially important in mixed-sediment environments like the Elwha River delta, where sediment varies dramatically over space and time and is difficult to separate using traditional image-based methods. In this study, SegmentationGym was used to classify beach surface imagery into three sediment

categories—sand, gravel, and cobble—as well as an organic material class and two additional classes representing scale bars and other non-sediment features. The model learns directly from the image data by picking up patterns in color and texture to identify sediment type rather than relying on manually defined image features or grain delineation. This makes it well suited for mixed-sediment environments, where overlapping grains and complex surfaces can limit traditional segmentation and statistical image methods.

2.2.3 Loss Function and Optimization

The SegmentationGym model used in this study consists of a SegFormer architecture trained using a standard cross-entropy loss function for multiclass segmentation, which measures the difference between predicted class probabilities and the true labels. Initial model performance on the validation set is summarized in Table 2.1, which highlights class imbalance and uneven performance across sediment types.

A hybrid loss function was tested as an attempt to improve performance on class imbalances and improve segmentation consistency. Standard cross-entropy loss tends to be dominated by more common classes which means it tends to reduce performance on smaller classes (like the scale bar in this study). Combining cross-entropy with a focal or dice loss can place more weight on harder-to-classify pixels and class overlap, which in theory should improve metrics such as IoU and MCC. The custom loss function was applied during model compilation which tested various combinations of loss parameters (α and γ) as well as class weighting.

Across all tested configurations the performance changes were marginal and did not lead to consistent improvements over the baseline model (Table 2.1). Although some configurations slightly improved class-weighted metrics, these improvements were not consistent across metrics. Overall, the results suggest that modifying the loss function alone was not sufficient to improve segmentation performance, and that model behavior is more strongly influenced by class structure than by loss formulation. This suggests that changing the loss function alone was not enough to address class imbalance, so the next step was to test an

ensemble approach that combines outputs from two models to improve class balance and overall model performance.

2.2.4 Ensemble Model Approach

To address the persistent class imbalance in the scale bar class, an ensemble model approach was used by training two models on the same image set. A binary model was trained to identify the scale bar (class 1) versus everything else (class 0), since this class was consistently misclassified in the multiclass model. A multiclass model was simultaneously trained to classify the rest of the sediment classes (sand, gravel, cobble, and organic debris). The final model output was then created by overlaying the binary scale bar mask onto the multiclass segmentation ensuring that the scale bar pixels were preserved regardless of how the multiclass model performed.

The scale bar was the most imbalanced and consistently misclassified class in the original multiclass setup. Treating it as a separate binary classification improved its detection while allowing the multiclass model to focus on sediment classification. The ensemble approach combines the outputs of these two models, improving overall class balance and segmentation performance metrics (Table 2.1). The results show consistent performance between the validation and testing datasets and an overall improvement over the original multiclass model. An example of the final ensemble output is shown in Figure 2.5, which overlays the predicted class labels on a representative image.

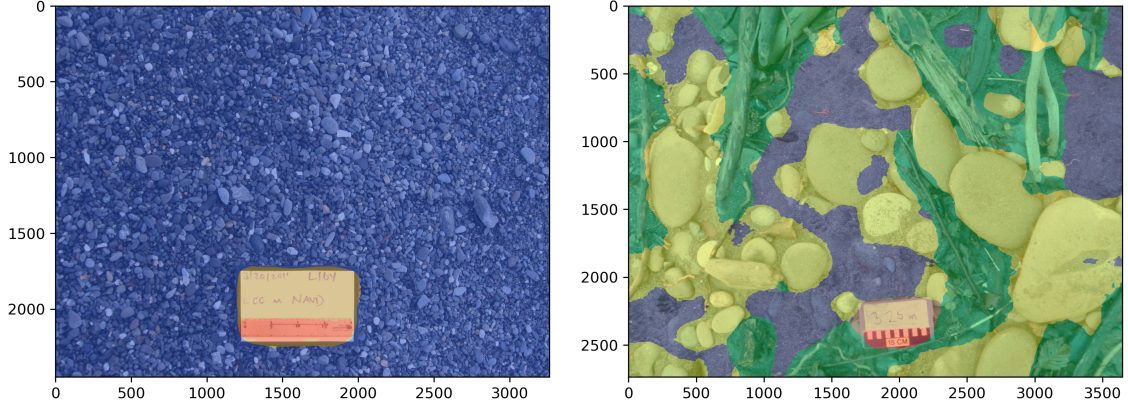


Figure 2.5: Example sediment classification produced by the final ensemble model. Predicted sediment classes are overlaid on the original shoreline imagery.

2.2.5 Model Performance Evaluation

To evaluate model performance, the following metrics were used:

Overall accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2.1)$$

Intersection over Union (IoU):

$$\text{IoU} = \frac{TP}{TP + FP + FN} \quad (2.2)$$

Mean IoU:

$$\text{mIoU} = \frac{1}{N} \sum_{i=1}^N \frac{TP_i}{TP_i + FP_i + FN_i} \quad (2.3)$$

Frequency-weighted IoU:

$$\text{FWIoU} = \sum_{i=1}^N \frac{n_i}{\sum_{j=1}^N n_j} \cdot \frac{TP_i}{TP_i + FP_i + FN_i} \quad (2.4)$$

Matthews Correlation Coefficient (MCC):

$$\text{MCC} = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (2.5)$$

Table 2.1: Summary of model performance across experiments

Model	Accuracy	mIoU	FWIoU	MCC
Baseline	0.75	0.63	0.35	0.52
Hybrid Loss (best)	0.71	0.63	0.37	0.55
Ensemble	0.82	0.75	0.42	0.60
Ensemble (Test)	0.76	0.66	0.43	0.49

Initial model performance is summarized in the first row of Table 2.1. The baseline model shows moderate accuracy, but comparatively lower IoU values indicate class imbalances and uneven performance across sediment types.

Across all tested loss function configurations, the overall performance remained similar to the baseline model (Table 2.1). Although some configurations showed minor improvements in individual metrics, these were not consistent across all evaluation metrics.

The ensemble approach showed improved performance relative to both the baseline and hybrid loss configurations (Table 2.1). Performance was consistent between validation and testing datasets, with an overall increase in accuracy of more than 7% compared to the original multiclass model.

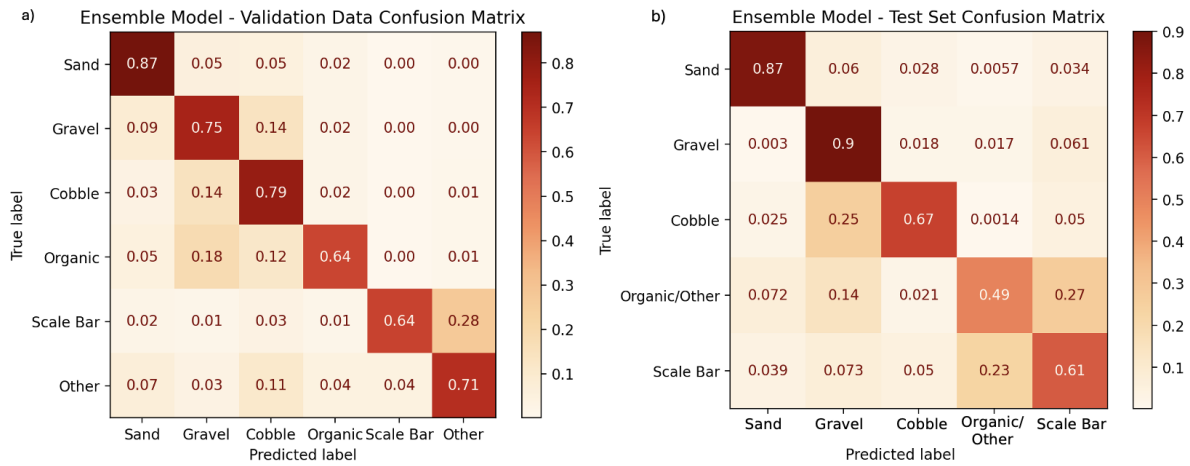


Figure 2.6: Confusion matrices showing ensemble method performance on validation ($n=102$ images) and testing ($n=30$ images) datasets. Values represent the percentage of pixels assigned to each predicted class.

In the validation confusion matrix (Figure 2.6a), the highest percentage of sediment misclassifications occurred between gravel and cobble, which is likely due to their similar textures in the imagery. In contrast, sand showed higher classification accuracy because of its more uniform appearance. As a result, gravel and cobble were grouped together as a single coarse sediment class, allowing the analysis to focus on the contrast between sand and coarser sediment. This reduces uncertainty caused by confusion between gravel and cobble and allows for clearer comparisons between sand and coarse sediment.

In the test set confusion matrix (Figure 2.6b), gravel and sand show the highest classification accuracy, while cobble is most frequently misclassified as gravel. This is likely a result of the test set containing a higher proportion of edge cases and complex conditions, including overlapping grain sizes, mixed sediments, shadows, and organic material, which make cobble more difficult to distinguish from gravel.

2.2.6 Scale Bar Detection and Measurement

Across the entire image dataset, nine different scale bar types were used when creating the image dataset. These scale bars vary in physical length (either 15 cm or 20 cm) and show small differences in aspect ratios. To extract grain sizes from these segmented images, measurements were standardized by identifying and converting the scale bars into pixel-to-centimeter ratios using a Python-based image processing workflow. For each image, a mask was created for the “scale bar” class, and a bounding region was extracted using the minimum and maximum pixel coordinates of the detected area (Figure 2.7). The width-to-height ratio of this region was then calculated and used to distinguish between scale bar types, since each configuration has a slightly different aspect ratio.

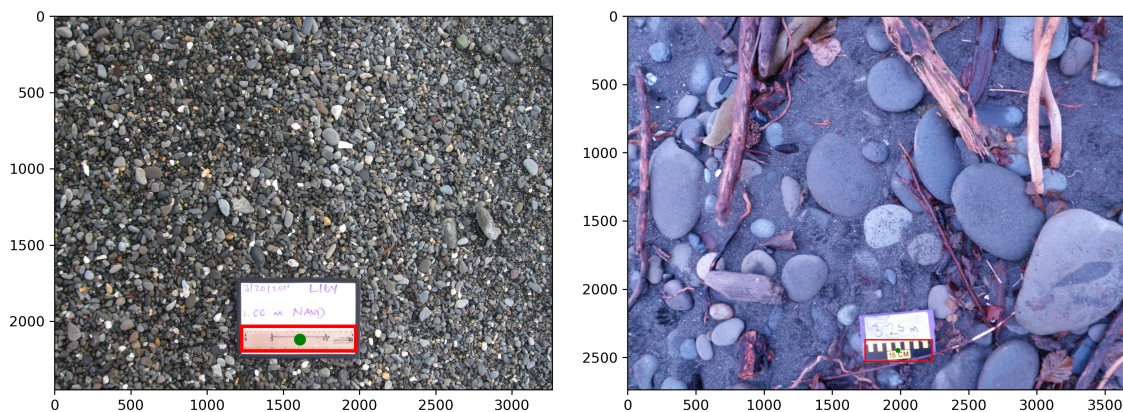


Figure 2.7: Example scale bar identification. The segmented scale bar mask is extracted from the classification and used to determine pixel-to-centimeter conversion.

Once the scale bar type was identified, a pixel-to-centimeter conversion factor was calculated based on its known physical length. This allowed pixel measurements to be converted into real-world units, which provided a consistent spatial scale across the full dataset. This step is important for interpreting segmentation results and provides the foundation for future work to extract grain-size distributions directly from imagery. For example, if indi-

vidual grains within a sediment class could be identified and measured using an automated approach, this would provide the means to convert grain sizes from pixels to millimeters.

2.3 Post-Processing and Classification

Following model training, the final ensemble model was used to segment each image in the dataset ($\sim 7,300$ images), generating pixel-based sediment statistics. The dataset was organized by transect and survey year and separated into summer and winter periods.

For each image, the segmentation output was used to calculate class percentages from the pixel-based classifications. These values were then used to calculate a normalized sediment metric, which represents the proportion of sand relative to all sediment classes, while excluding the three classes of non-sediment pixels: scale bar, organic material, and other. Grouping gravel and cobble into a single coarse sediment class allows the analysis to focus on the contrast between sand and coarser material. This approach also assumes that higher sand content reflects the material released during dam removal, since much of the sediment transported to the delta after removal consisted of finer grains. This metric provides a consistent way to compare sediment composition across the dataset and track changes in beach coarseness through time.

To support spatial interpretation, an interactive, web-based mapping tool was developed to visualize percent sand along each transect for each survey year (Figure 2.8). This provides an interactive representation of alongshore change in sediment composition across the Elwha River delta.

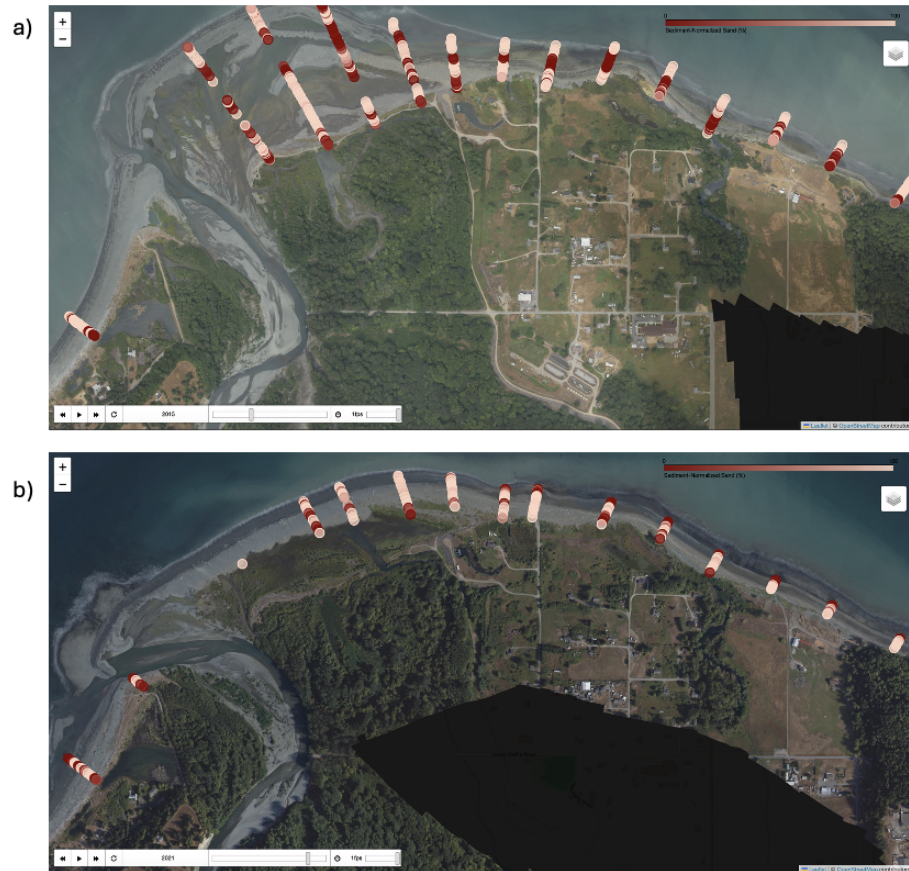


Figure 2.8: Web Maps showing percent sand for each point along the shoreline in 2015 (a) and 2021 (b). These illustrate spatial changes in sediment composition following dam removal.

2.4 Data Limitations

Several limitations were identified in the dataset and image classification workflow. The sediment imagery shows inconsistencies in light, shadows, and partial coverage by water or organic material, which can obscure sediment and create classification inconsistency across the dataset. In addition, multiple scale bar types were used throughout the entire survey period. These differed in shape and length, which affected model performance during training and required additional post-processing to standardize measurements.

Confusion between gravel and cobble was also a limitation in the classification results. These two classes share similar textural characteristics and can appear visually similar depending on image scale and resolution. In the Elwha dataset, sediment misclassification was most common between gravel and cobble, although this could change depending on local grain-size distributions. These limitations motivated the grouping of gravel and cobble into a single coarse sediment category for analysis.

Chapter 3

RESULTS

The performance of the final segmentation model is summarized in Table 2.1. The similarity between validation and testing metrics indicates that the model performed consistently on new images and was not strongly overfit to the training data. This performance was considered sufficient to resolve the differences between sand and coarse sediment. The model was applied to the full topobathymetric image dataset to evaluate sediment change from 2011 to 2023.

Class-specific accuracy metrics are shown in the confusion matrices in Figure 2.6. Sand was the most reliably classified sediment type and contained relatively few misclassifications. The most frequent errors occurred between gravel and cobble, which have similar visual characteristics and are difficult to distinguish at varying image scales. These results were used to analyze sediment composition and its spatial, temporal, and elevation variability across the full dataset.

3.1 Sediment Class Composition

Class composition was calculated as the percentage of pixels assigned to each class within each image. These values were aggregated by survey period (annual summer or winter survey) and averaged to characterize the temporal variability across the Elwha River delta.

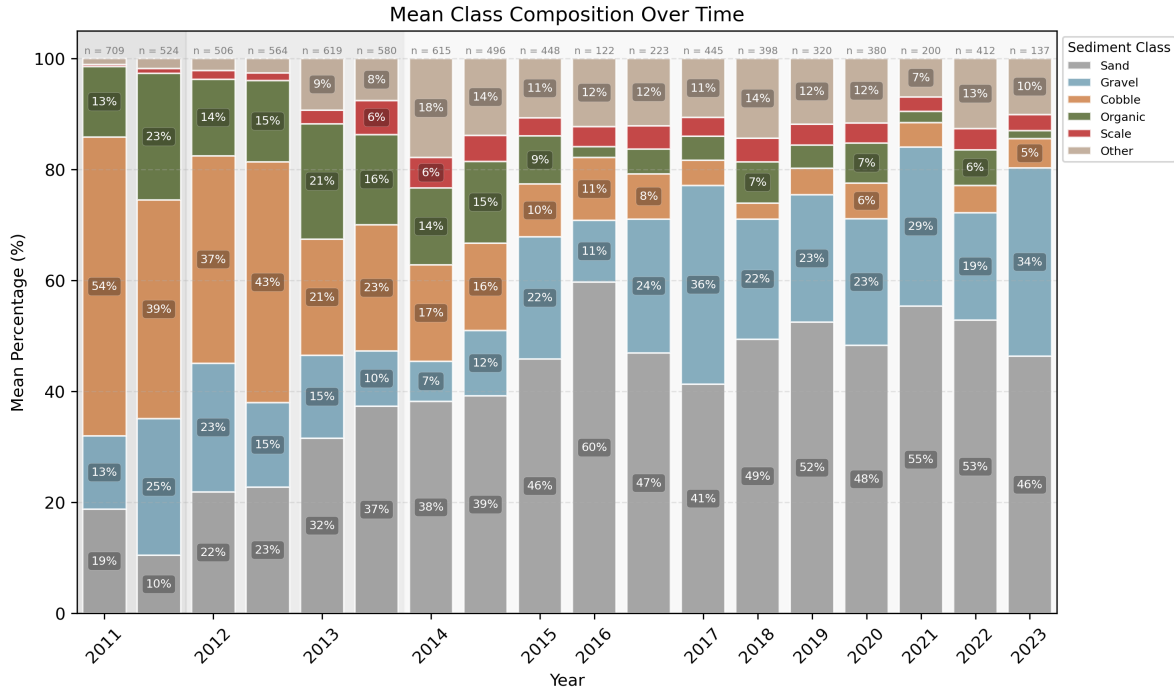


Figure 3.1: Bar chart showing average survey class composition percentages as an average of all classified pixels.

Sediment composition shifted significantly following dam removal (Figure 3.1). During the pre-dam removal period, the shoreline was dominated by coarser sediment, with sand comprising less than 20% of classified pixels on average and gravel and cobble together accounting for approximately 60%. During the dam removal period, sand percentages increased substantially, reaching approximately 40–60% of pixels, while the proportion of coarse sediment declined. This trend highlights the transition from a cobble-dominated shoreline to a more mixed gravel and sand environment. This fining of the sediment likely reflects the delivery of a large volume of sand to the coast following dam removal [23] and its subsequent transport away from the river mouth [30]. The apparent decrease in cobble may indicate the burial of coarse material by newly deposited sand.

In addition to shifts in sediment fractions, organic material shows a slight decrease from

pre- to post-dam removal conditions. This decline could reflect the burial of newly deposited sediment or changes in the accumulation of organic debris as the shoreline evolved following dam removal. Because organic material was not analyzed separately, the cause of this decline remains uncertain.

3.2 Alongshore Sediment Distribution

To characterize spatial and temporal sediment trends, sand was expressed as a percentage of the total classified sediment. Gravel and cobble were grouped into a single coarse sediment class to reduce uncertainty gravel-cobble misclassifications. This grouping is also important because sand is generally more mobile than gravel and cobble. The survey data also includes alongshore transect measurements, which allowed for spatial variability analysis along the shoreline.

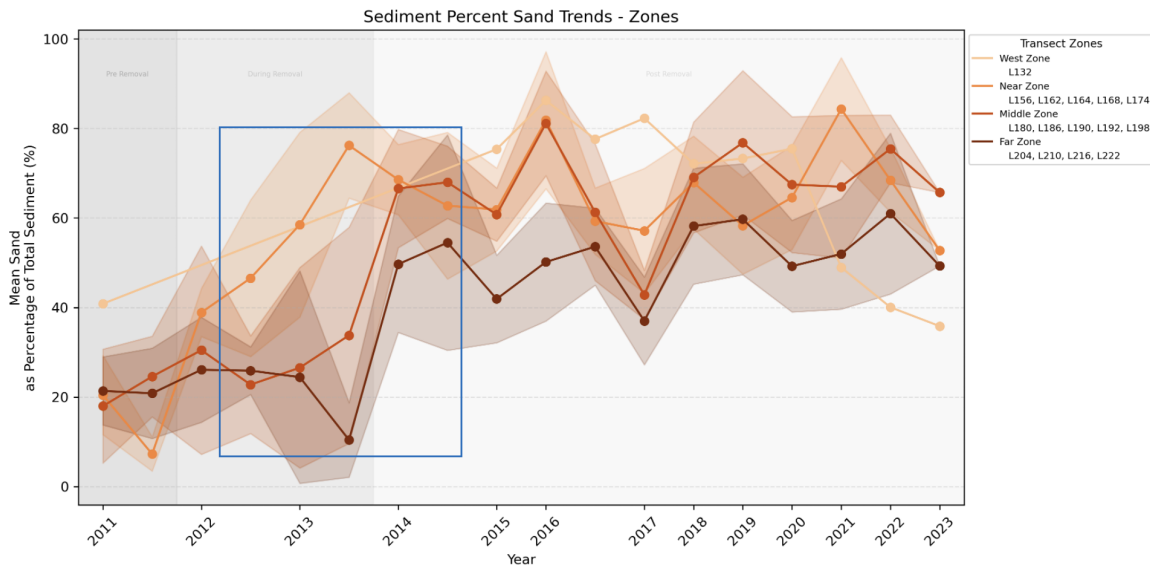


Figure 3.2: Mean sand percentage through time by alongshore transect zone. Shaded regions represent ± 1 standard deviation of percent sand.

Sand percentages varied through time across the survey period and differed by transect group (Figure 3.2), with transects grouped into the West Zone (west of the river mouth), Near Zone (immediately east of the river mouth), Middle Zone (central transects), and Far Zone (most distal from the river mouth). The annotated box around the 2012–2014 survey periods highlights an alongshore lag in sand percentage increase, where the Near Zone responded first in 2012–2013, followed by the Middle Zone around 2013, and then the Far Zone beginning in 2014.

Following this initial increase, sand percentages began to stabilize and show less variability in the later survey years. The sharp increases observed in the Near and Middle Zones gradually level off after their respective peaks, and the Far Zone shows a lower overall sand content and more muted response. Under the assumption of relatively consistent sand thickness, these patterns suggest that sediment continued to spread alongshore after the initial surge, with the largest changes occurring closest to the river mouth.

Transect L132 in the West Zone follows a similar overall trend to the other zones before sand percentages drop significantly starting in 2020 (Figure 3.2). This coarsening is a reflection of the transect being taken over by the shifting of the river mouth (Figure 3.3).



Figure 3.3: Plane Cam images of the river mouth shifting between 2019 and 2021. Reproduced from [24].

3.3 Cross-Shore Sediment and Elevation Trends

Cross-shore changes in sediment composition were examined to characterize how sand and coarse sediment were distributed across the beach profile following dam removal. These trends were analyzed by elevation zone and through representative cross-shore transect profiles to evaluate how sediment composition varied with elevation and distance from the river mouth.

3.3.1 Elevation Zone Trends

To examine how sediment composition varies with shoreline elevation, survey image elevation data was grouped into three elevation zones based on Elwha tidal datums: below mean lower low water (<MLLW), an "active beach" between MLLW and mean higher high water (>MHHW), and above MHHW. This grouping allows sediment composition to be compared along the cross-shore profile under different coastal conditions.

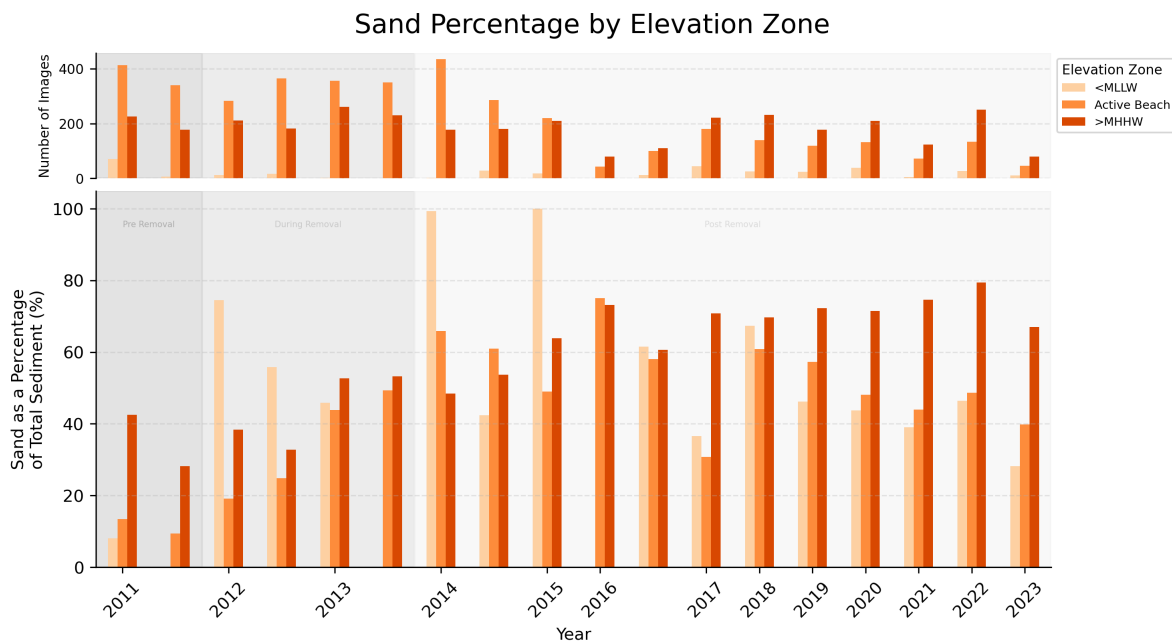


Figure 3.4: Bar chart showing trends in elevation profiles throughout the dataset

Sand percentages varied through time across elevation zones along the shoreline (Figure 3.4), with relatively low percentages prior to dam removal, particularly in the lower and active beach zones. Around 2013, sand percentages rapidly increased within the active beach and lower-elevation ($< \text{MLLW}$) areas, corresponding to major sediment release from dam removal. In the later post-dam removal years, the supratidal ($> \text{MHHW}$) zone also began showing higher percentages of sand. This suggests that sand initially accumulated in the active beach before being gradually redistributed to higher elevations through overwash, wave runup, and other cross-shore transport processes.

Unlike the subtidal and active beach, where sand percentages began to decline after 2016, the upper beach remained relatively sandy throughout the later survey years. The persistence of sand at higher elevations suggests that sediment remained stored within the supratidal zone. These conditions may have helped support the expansion of vegetation that was observed in later years.

The active beach zone contains the largest number of observations throughout the survey record and shows the strongest yearly variability in sand percentages. In contrast, there is less frequent survey coverage below MLLW throughout the survey period, though the data that does exist indicates a significant increase in sand percentages during dam removal.

3.3.2 Representative Cross-Shore Profiles

Cross-shore elevation profiles were examined to evaluate how sand and coarse sediment were distributed across the beach profile through time following dam removal. For each transect, DEM elevation profiles were paired with sediment classification results to show how sand percentages varied across the cross-shore profile for each survey period. Figures 3.5–3.7 show representative examples of how cross-shore profiles evolved at different locations along the shoreline, including areas just east of the river mouth, within the middle reach, and farther east alongshore. These profile changes are also a reflection of how wave energy varies spatially and the impact on cross-shore sediment redistribution.

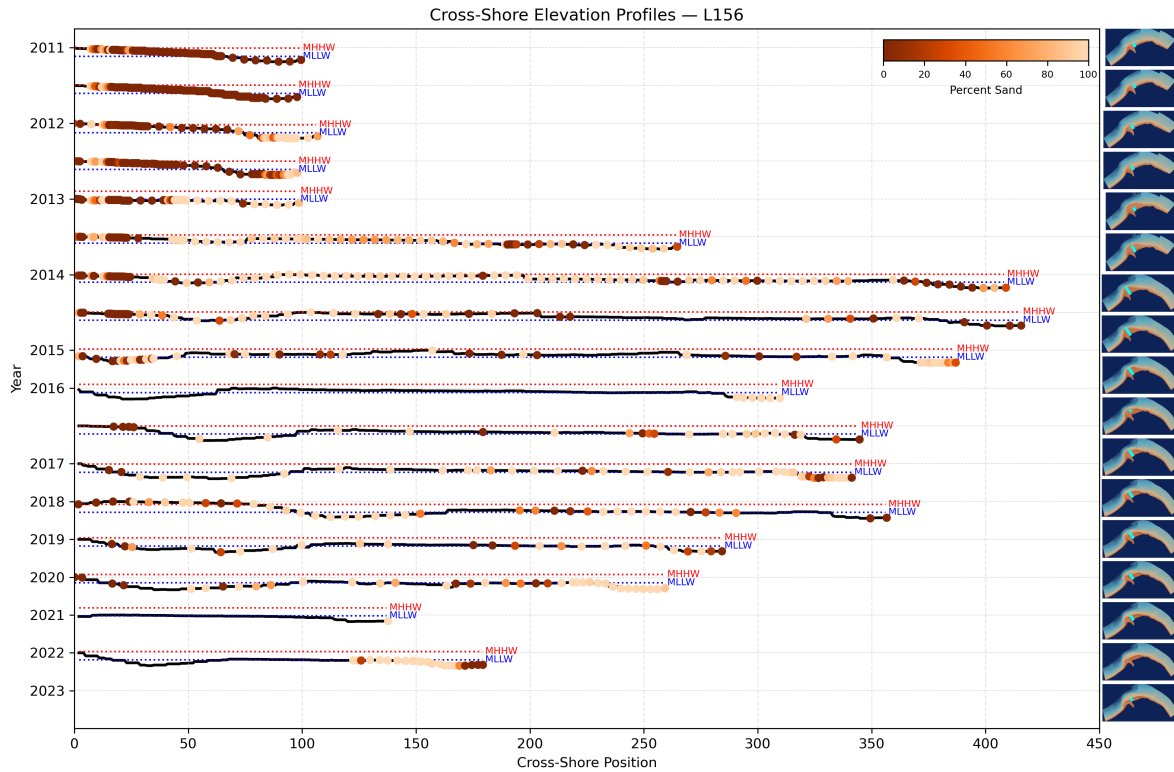


Figure 3.5: Cross-shore elevation profile and sand percentage for transect L156 (near river mouth).

Transect L156 (Figure 3.5, closest to the river mouth) showed the largest increase in sand content following dam removal. Sand percentages increased across much of the profile, especially at lower elevations where the largest amount of new sediment was deposited. Compared to the other transects, changes occurred earlier and were more substantial near the river mouth.

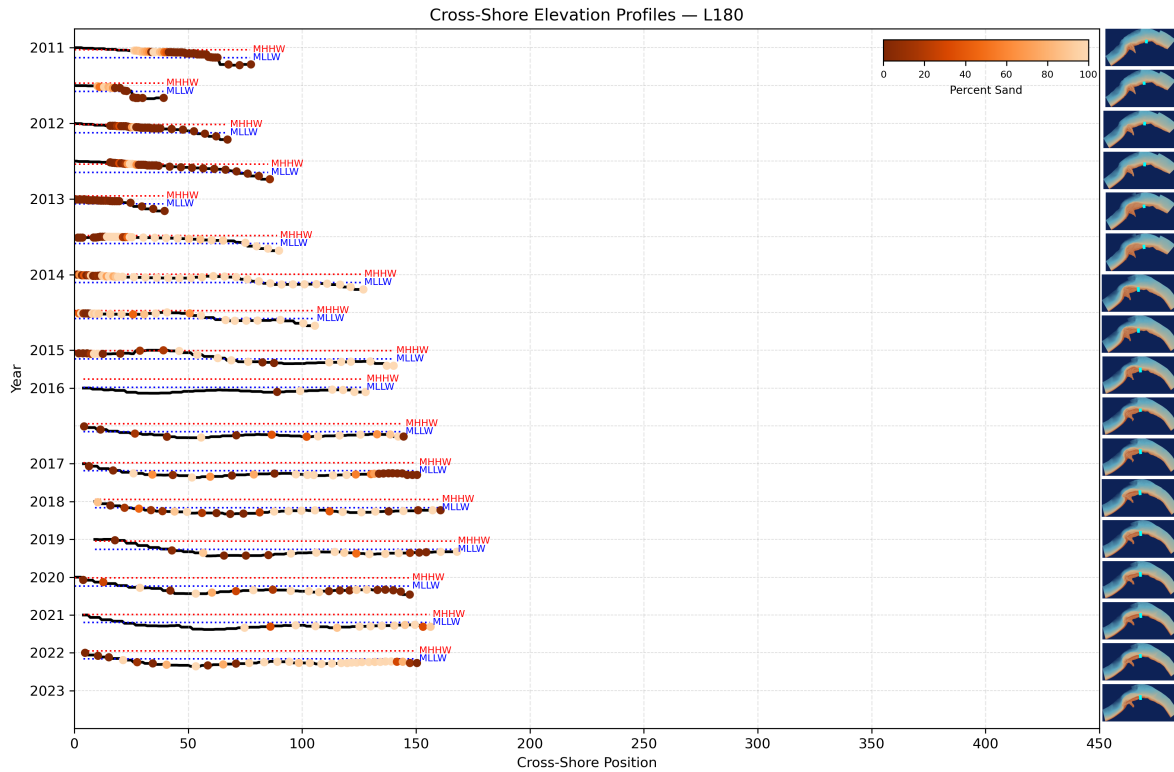


Figure 3.6: Cross-shore elevation profile and sand percentage for transect L180 (middle reach transect).

Transect L180 (Figure 3.6, middle zone) represents a different response. During the dam removal period, sand percentages increased significantly through the active and lower beach elevations. Post dam removal, the profile became more mixed, with alternating sandy and coarse sections appearing across the transect. Compared to the near-mouth transect, these changes occurred later in the survey record and were smaller in magnitude.

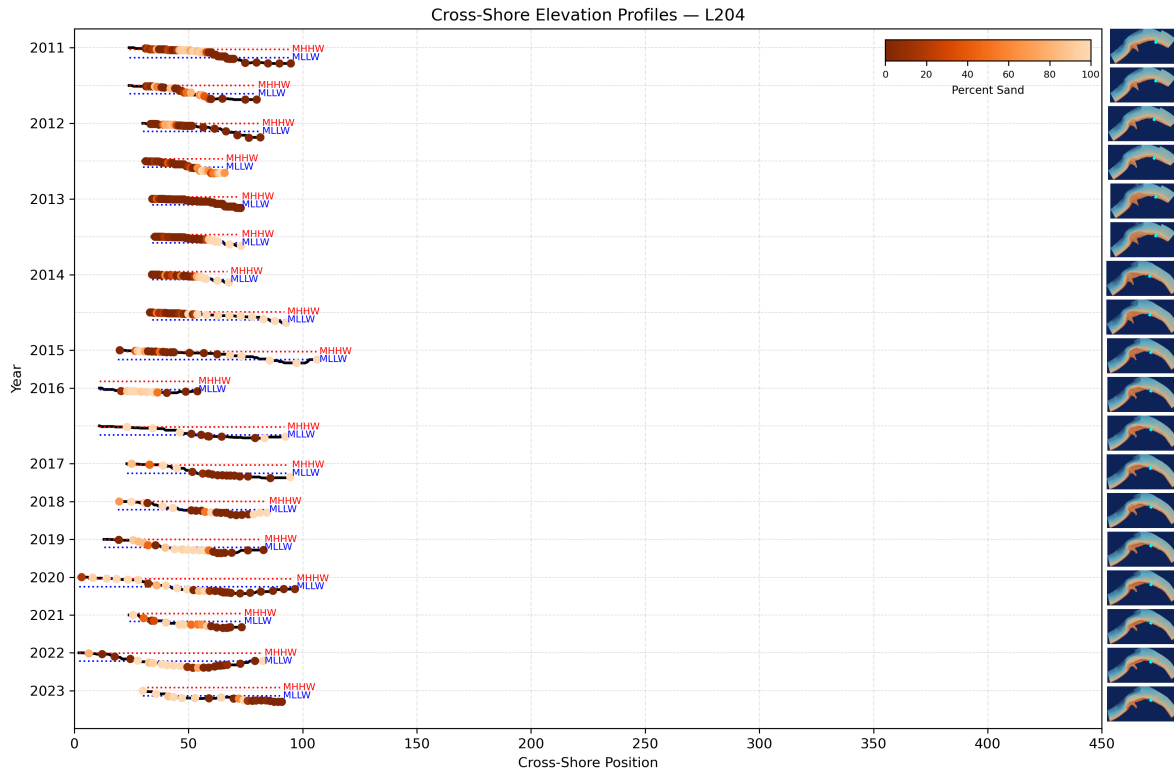


Figure 3.7: Cross-shore elevation profile and sand percentage for transect L204 (far reach transect).

Transect L204 (Figure 3.7, far zone) shows the smallest and most gradual increase in sand content through time. Beginning around 2014, sand percentages increased first within the lower and active beach and later became more common in the upper beach. These changes were smaller and less consistent than those observed farther west, and the profile remained relatively coarse throughout the study period. This pattern suggests that wave run-up and setup reworked sand into higher beach elevations as the beach profile adjusted.

Together, these profiles show an alongshore trend where sediment changes were strongest near the river mouth and decreased farther alongshore. Areas closer to the river mouth experienced earlier and larger increases in sand content following dam removal, while eastern transects showed a slower and more gradual response over time. These patterns are consistent

with the general trends in topographic change reported by [30].

Chapter 4

DISCUSSION

4.1 Coupled Morphology–Sediment Response

Morphological change derived from DEMs was compared with survey sediment composition data (both filtered to the active beach $> \text{MLLW}$ and $< \text{MHHW}$) to examine how beach morphology and surface sediment evolve together across the Elwha River delta. For each dataset, a corresponding rate-of-change time series was generated relative to the first survey, allowing these morphological and sediment changes to be analyzed relative to pre-dam removal baseline conditions.

4.1.1 Morphological Change

DEM data was used to quantify changes in beach volume alongshore over time. Spatial and temporal variability in erosion and deposition across the delta is captured in the space-time plot (Figure 4.1), which aggregates volume change over the study period. A corresponding rate-of-change plot is also shown, which highlights periods of accretion and erosion relative to the 2011 baseline.

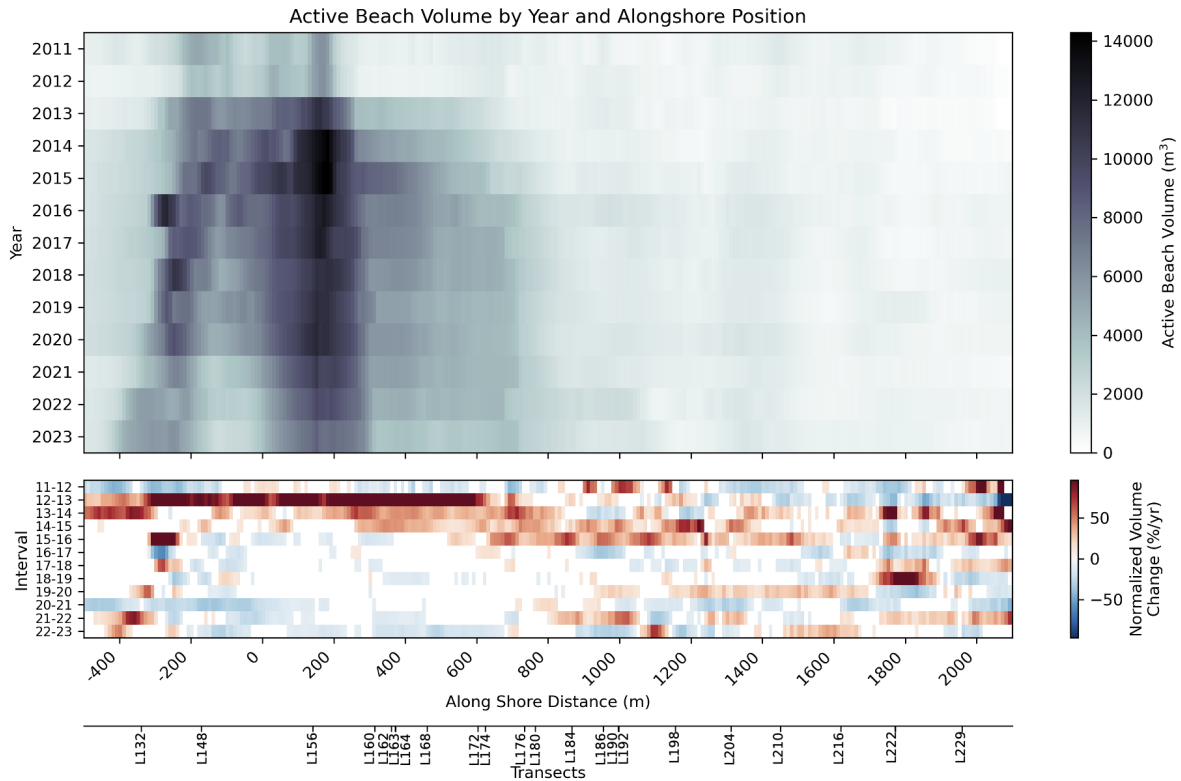


Figure 4.1: Space-time plot showing DEM-derived volume change along the shoreline. Colors indicate areas of sediment accretion and erosion through time.

Most of the measurable increase in beach volume on the active beach was concentrated immediately east of the river mouth (Figure 4.1), with volume increases peaking after dam removal in the years immediately following sediment transport to the delta. Farther east, beach volume was generally lower and changed less through time. The normalized rate-of-change panel (lower subplot) shows periods of accretion (red) and erosion (blue) that varied along the shoreline between survey years. The largest accretion signals occurred in the years after dam removal, while later years indicated mixed patterns of erosion and deposition. Overall, the space-time plot highlights that sediment accumulation was strongest near the river mouth during dam removal, propagated alongshore in the years immediately following dam removal and then varied alongshore and through time after approximately 2017, perhaps

reflecting the propagation of sediment waves as discussed in Warrick et al [30].

4.1.2 Sediment Composition Change

Simultaneously, sand percentage was quantified from the classified imagery and aggregated at each transect for each survey. Percent sand is summarized in a space-time plot (Figure 4.2a), with a second panel showing rate of change relative to each transect's baseline survey. This shows the spatial and temporal variability in sediment composition across the delta, as well as significant rates of change throughout the survey period.

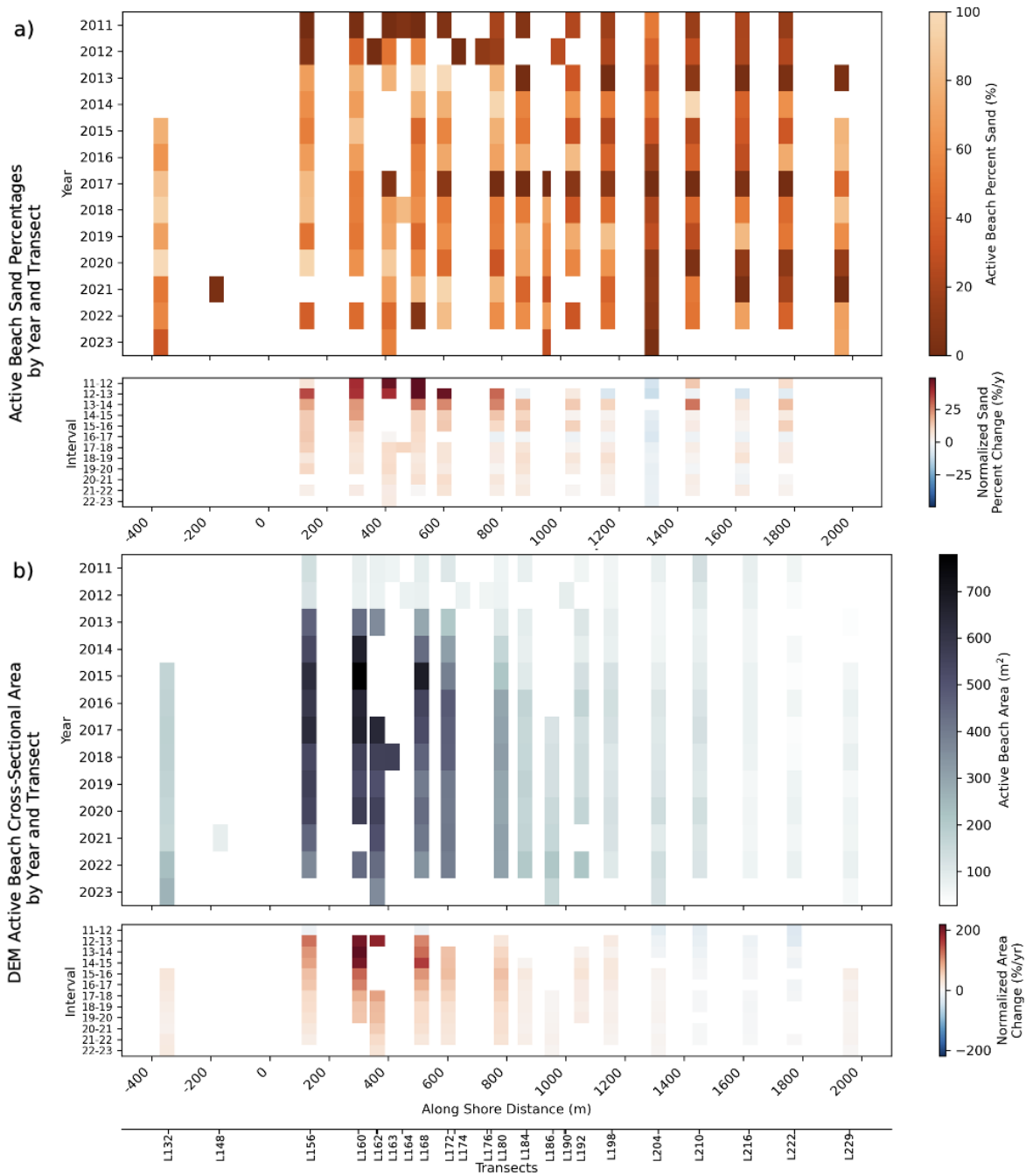


Figure 4.2: Space-time plots showing (a) percent sand along shoreline transects and (b) DEM-derived area aligned with the same transects.

A clear increase in sand around 2012 was concentrated just east of the river mouth (Figure 4.2a). Over the following years, this signal propagated progressively farther east, with increasing lag as distance from the river mouth increased alongshore. The pattern suggests that the strongest response occurs closest to the river mouth, with conditions shifting eastward along the shoreline over time.

The change rate panel (Figure 4.2b) corroborates this theory, showing a strong early increase in sand near the mouth followed by smaller and more variable changes further downshore. The two panels suggest that post-dam removal sediment distribution was strongest near the river mouth and became weaker and less consistent with distance, reflecting how sediment traveled along the shoreline over time.

4.1.3 Morphology–Sediment Comparison

To directly compare morphological and sediment change, annual DEM elevations were extracted along each transect (Figure 4.2b). The active beach cross-sectional area was then calculated by integrating the elevations between MLLW and MHHW along the profile. This allowed changes in beach morphology and sediment composition to be compared at consistent alongshore locations.

Extracting DEM elevations along each transect allowed direct comparison between changes in beach morphology and sand percentages. The change rate for the transect-aligned DEM space-time plot (Figure 4.2b) is useful for comparison with the sediment percent sand results, since it highlights where and when changes occurred more clearly than the raw values do. It shows early increases in sediment volume near the river mouth after dam removal, and more variable changes farther downdrift over time.

4.1.4 Correlation

Pearson correlations between the normalized DEM-derived area change and the normalized percentage of sand change were calculated to quantify the relationship between the rates of

change shown in the space-time plots. The analysis was separated by transect zone (West, Near, Middle, Far) to assess how this relationship varies spatially along the shoreline.

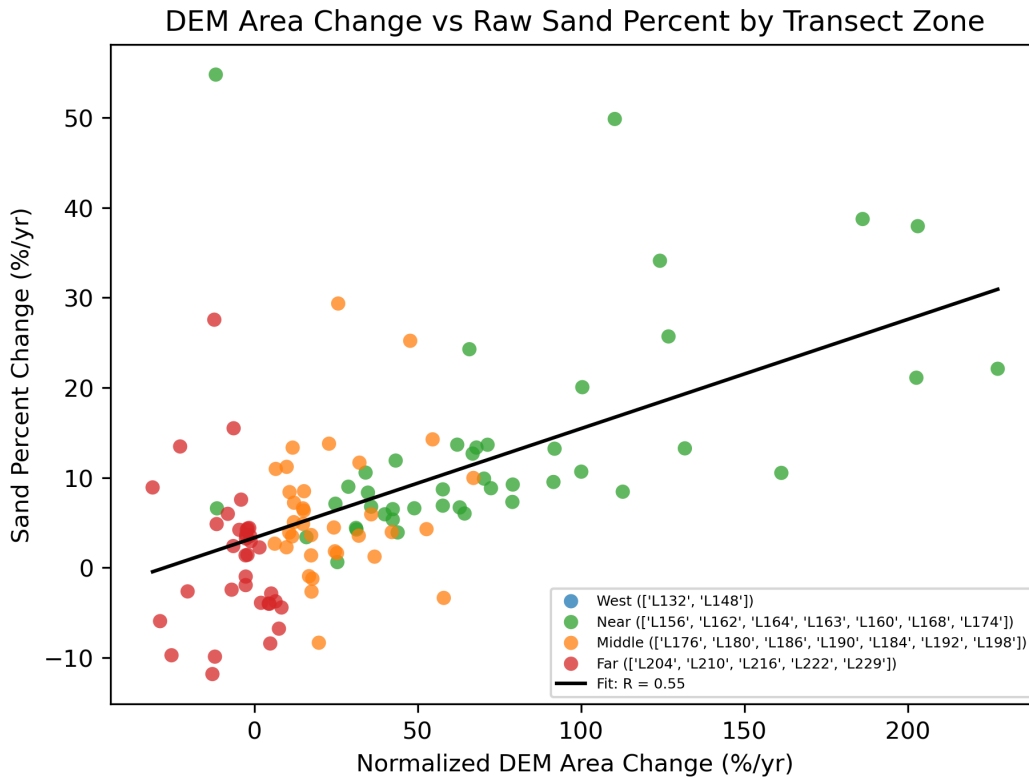


Figure 4.3: Correlation between morphological and sediment change rates.

A positive Pearson correlation is observed between the change rates ($R = 0.55$) (Figure 4.3), suggesting a relationship between increases in cross-sectional area and increases in sand content. This relationship suggests that beach growth following dam removal was often associated with increases in sand content. However, the moderate correlation suggests that coarse sediment also contributed to morphological changes. Overall, the correlation between morphological and sand content change was strongest closer to the river mouth, where sediment deposition was greatest, and became more variable farther alongshore.

Overall, the DEM-derived morphology and sediment composition analyses indicate that

shoreline evolution following dam removal was strongly coupled to changes in sediment composition. Transects that experienced the largest increases in sand percentage also showed the greatest increases in sediment area and shoreline progradation, particularly near the river mouth. The timing of coarse-to-sand transitions also follows this pattern. Transects that showed the earliest increases in sand were generally the same sections that showed the greatest shoreline growth after dam removal. Together, these results suggest that the large sediment pulse released during dam removal shaped both shoreline morphology and sediment composition across the delta. However, the far zone showed increases in sand content despite relatively small morphological changes, suggesting that sediment composition continued to evolve after shoreline growth slowed. As a result, ecological responses to dam removal can occur even in areas where morphological change is limited.

4.2 Sediment Arrival and Alongshore Propagation

4.2.1 Coarse-to-Sand Transition

To quantify the timing of sediment change alongshore, and to relate these results to those in Warrick et al [30], a coarse-to-sand transition was defined within the active beach zone ($> \text{MLLW}$ and $< \text{MHHW}$) as the first survey period in which sand percentage increased by at least 30% relative to the initial sand percentage for each transect.

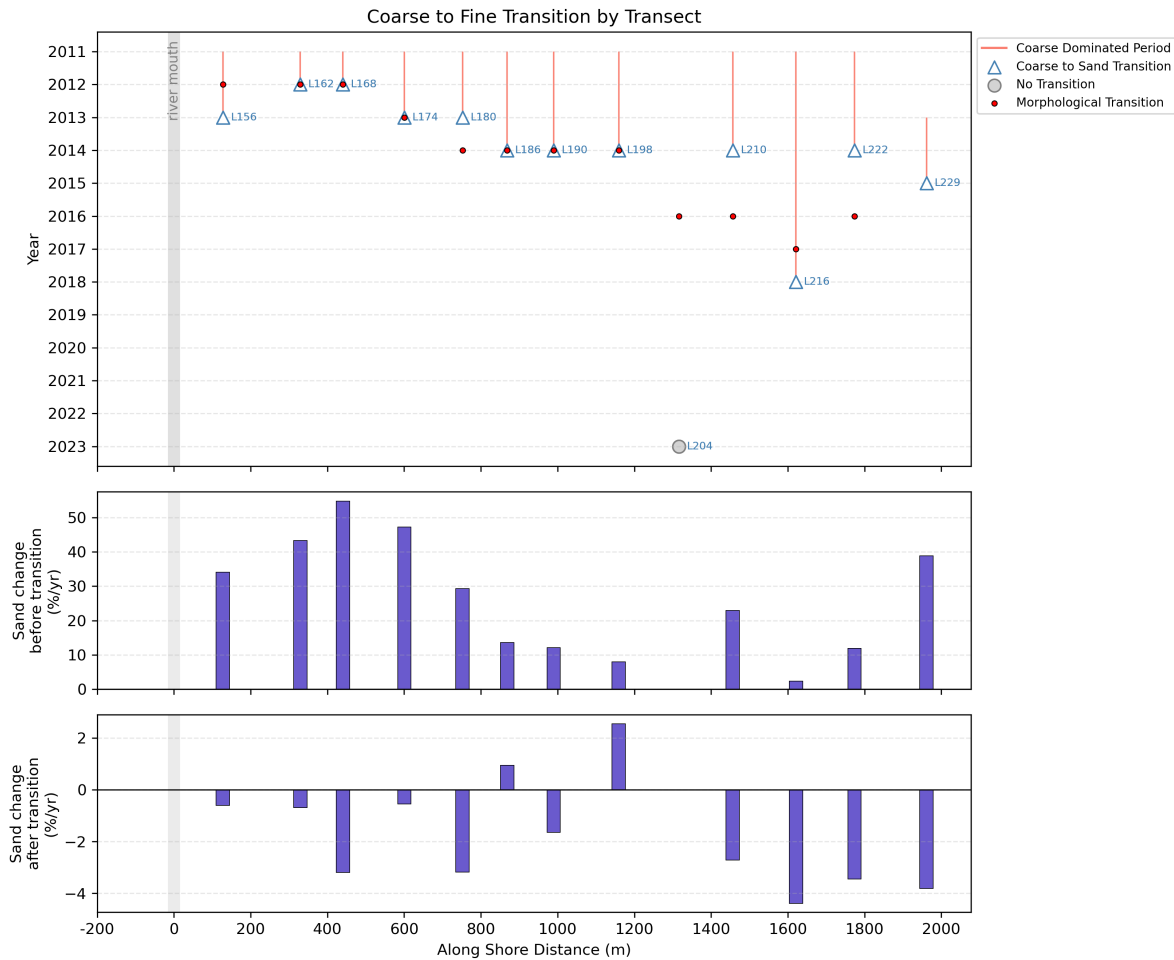


Figure 4.4: Timing of coarse-to-sand transitions by transect.

Timing of coarse-to-sand transitions for each transect within the active beach zone (Figure 4.4) suggests alongshore differences in the response to dam removal, and a west-to-east propagation of the sediment composition response associated with dam removal. Transects closest to the river mouth transitioned from coarse-dominated to sand-dominated conditions earlier, generally between 2012 and 2013, while more eastern transects transitioned later, between 2014 and 2019. A few transects throughout the shoreline either did not transition during the study period and remained predominantly coarse, or did not have enough survey years to meet the criteria for a transition period. The middle panel shows that rates of change

from coarse to sand prior to transition year were generally highest in transects near the river mouth and decreased farther alongshore. In contrast, rates of change after transition were smaller and frequently negative, indicating that sand percentages stabilized or decreased slightly after the initial transition to sand-dominated conditions. Together, these results show that sediment changes following dam removal propagated alongshore through time, and that the strongest and earliest responses occurred closest to the river mouth. Also, this analysis suggests that the sediment composition change and the topographic change signal propagated at different rates alongshore in the Far zone of the delta.

4.2.2 Morphological Transition

The shift from coarse-dominated to sand-dominated conditions supports the alongshore movement of finer sediment across the delta. Transects closest to the river mouth transitioned first while more distant transects transitioned several years later. This spatial lag suggests that sediment released during dam removal was transported eastward over time.

The sediment change rates before and after the transition also show how shoreline response evolved over time. Before transition, transects near the river mouth experienced more rapid sediment deposition during the first few years of transport. After the transition, change rates were mostly negative, showing that this accumulation leveled off once transects became sand-dominated. The biggest shifts therefore happened during the dam removal period, and afterward, the delta shifted from sediment accumulation to mostly sediment redistribution along the shoreline. These lower rates of change likely reflect the system balancing out after the initial pulse of sediment.

This alongshore pattern (Figure 4.4) matches the morphologic and shoreline changes shown in Figure 4 (a-c) of [30] (Figure 4.5).

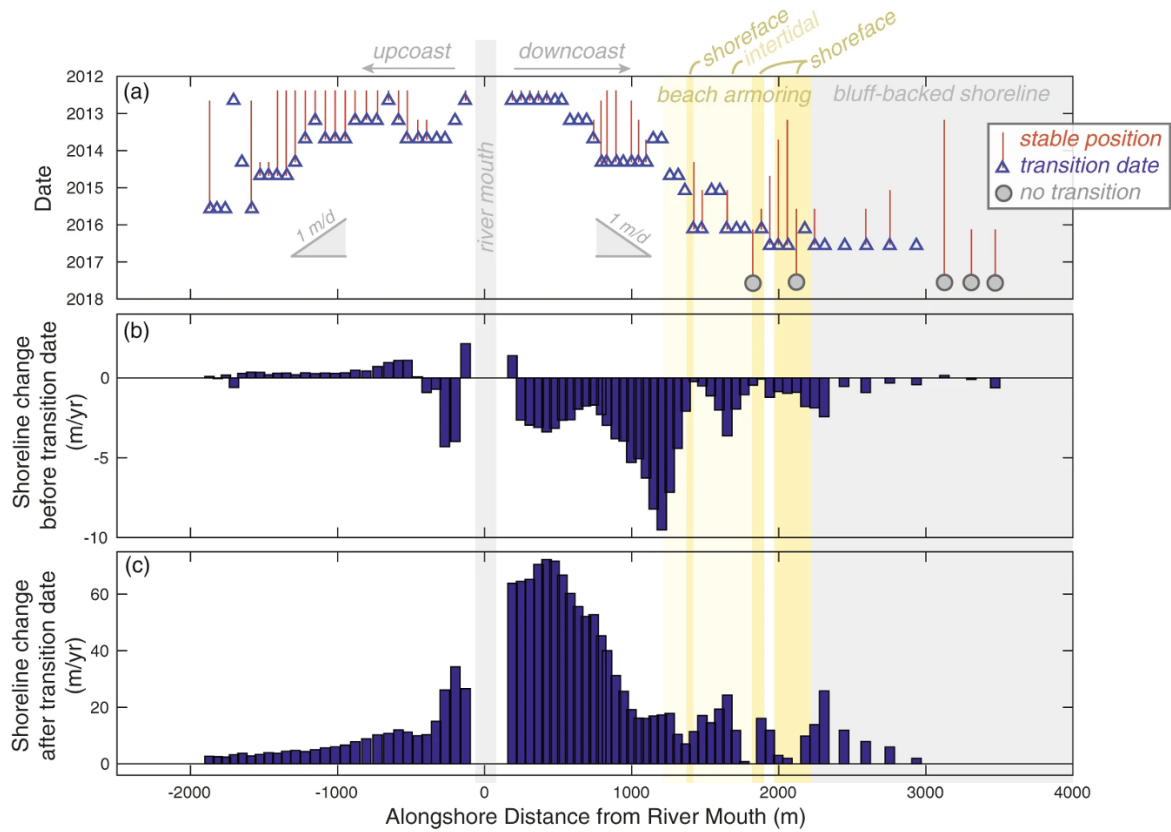


Figure 4.5: Observed shoreline response to dam removal at the Elwha River delta. Reproduced from [30]

Dam removal triggered a clear increase in sand across the Elwha River delta, which was progressively transported eastward away from the river mouth. Before dam removal, the delta was sediment starved and dominated by gravel and cobble. After removal began in 2011, a pulse of finer sediment was transported to the river mouth and propagated farther alongshore in later survey years. This pattern reflects the release of large sediment volumes being transported along the shoreline through the delta's littoral system.

Collectively, these results suggest that the coarse-to-sand transition captures a similar shoreline response to the topographic and morphologic changes observed in previous work [30].

4.3 *Cross-Shore Sediment Distribution*

Sediment changes can also be seen in the cross-shore beach profiles, which show that dam removal influenced both alongshore and cross-shore sediment transport. Sand percentages increased in all elevation zones following dam removal, particularly showing a strong and early increase in the active beach and supratidal ($>$ MHHW) zones. In contrast, changes in the lowest elevation zone had similarly strong peaks, but are more uncertain due to limited sampling. In later survey years, sand percentages in the active and lower-beach zones declined from their early peaks, while the upper beach generally remained sandy. The delayed increase of sand within the supratidal zone suggests that sediment was not deposited uniformly across the beach profile. Instead, sand first accumulated within the active beach before being redistributed to higher elevations over time. Wave runup, overwash, and storm-driven transport moved sediment into the upper beach. Once deposited, this sediment was retained and likely contributed to sediment storage and later vegetation growth.

Near the river mouth (Figure 3.5), the profiles indicate substantial shoreline progradation and seaward extension of approximately 400 m over the study period. Sand percentages increased across the profile, particularly at lower elevations where the largest amounts of new sediment were deposited. This response reflects the large volume of sediment released during dam removal that accumulated near the river mouth before being redistributed alongshore.

The middle transects (Figure 3.6) still show cross-shore accretion, but are much smaller with the shoreline prograding by only about 100 meters. Sand percentages increased throughout active and lower beach zones before the profile became more mixed later in the survey period. This suggests alongshore transport away from the river mouth combined with ongoing wave reworking.

In contrast, the far eastern transects (Figure 3.7) show little shoreline progradation and smaller increases in sand content, highlighting a much weaker morphological response as the distance from the river mouth increases. Despite the weaker overall response, sand became increasingly common at higher elevations over time, suggesting that even under lower wave-

energy conditions, wave run-up and setup redistributed sediment landward.

Throughout the survey period, these figures show that the sediment spread across the beach profile was being reworked rather than built up. The strongest changes stayed near the river mouth, while farther alongshore the beach profile remained relatively stable. These patterns show that beach evolution after dam removal varied spatially, with clear cross-shore progradation near the sediment source and smaller, but still measurable, morphological change at the distal end of the delta.

4.4 Combined Alongshore and Cross-Shore Processes

The results suggest that post-dam-removal evolution of the Elwha River delta was controlled by the combination of alongshore and cross-shore sediment transport (Figure 4.6). Alongshore transport redistributed the sediment that was released during dam removal away from the river mouth, which produced the eastward progression of transitions from coarse dominated to sand dominated transects. The strongest increases in sand percentages, sediment volume, and shoreline progradation all occurred closest to the river mouth.

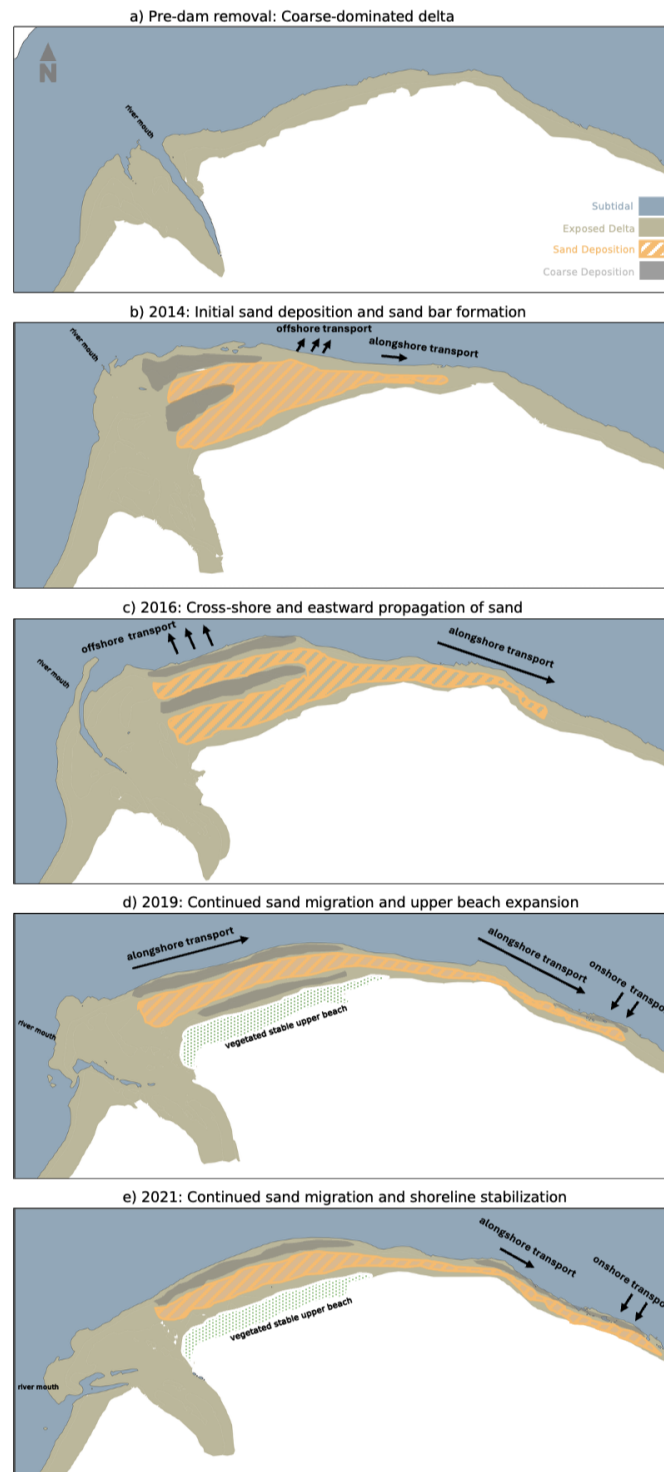


Figure 4.6: Conceptual model showing how alongshore and cross-shore sediment transport interacted during and after dam removal at the Elwha River delta.

Once sediment reached the delta, cross-shore processes redistributed it across the beach profile. Near the river mouth, sediment was transported offshore and formed nearshore sand bars. As the delta prograded offshore, sediment was retained in the supratidal zone which contributed to upper-beach stabilization and vegetation growth. Along the eastern transects, sand was gradually redistributed higher onto the beach profile while coarser gravel and cobble concentrated along the lower beach.

Together, these patterns indicate that alongshore transport controlled the delivery of sediment across the delta and cross-shore transport influenced where this sediment was being stored on the beach profile. The combined action of these processes produced the observed changes in sediment composition, shoreline morphology, and upper-beach stabilization following dam removal.

4.5 *Future Work*

As stated in Chapter 2.1, the full 15,000-image dataset included about 6,700 high-frequency images not used in this analysis. The topobathy dataset analyzed in this study provides a detailed semi-annual record that captures the dominant morphological and sediment changes following dam removal, but it does not resolve shorter-term variability caused by storms or tides. The higher-frequency dataset includes monthly surveys for four transects across the delta. Applying the same sediment classification and cross-shore analysis to this dataset would extend this work by connecting morphological trends to shorter-term sediment changes driven by storms, tides, and seasonal variability.

Extracting grain size from image segmentations is another potential extension for sediment analysis. The current analysis provides useful information on sand and coarse sediment distribution, as well as accurate scale bar pixel to centimeter ratios. However, it does not yet have the capacity to fully resolve grain-size information, which would allow for a fully detailed analysis of grain-size distribution and trends following dam removal.

Recent machine learning models such as SegmentEveryGrain [3] offer useful methodologies for extracting individual grain boundaries from imagery. Initial exploration of the

dataset in this study suggests that this method can successfully detect individual grains (Figure 4.7) and has potential for estimating grain-size distributions when combined with scale-bar conversion. However, initial analysis showed inconsistencies in grain density estimates relative to manual point-count methods, suggesting a need for further validation. Despite this limitation, SegmentEveryGrain provides a promising framework for future work to extract grain-size information from the Elwha river delta dataset with further refinement.



Figure 4.7: Example SegmentEveryGrain output for an ideal image from the Elwha River dataset.

Chapter 5

CONCLUSION

This research indicates that the Elwha river delta was transformed after a large pulse of sediment was released during dam removal. During the study period, changes in shoreline morphology and sediment composition propagated from the river mouth along the coast. Close to the river mouth, the delta expanded rapidly and sand percentages increased early on. Farther from the river mouth, changes in shoreline position, sediment volume, and composition were smaller and more delayed. Cross-shore, the sediment was reworked throughout the active beach during and after dam removal. The shoreline prograded and sediment volume increased in the lower and active-beach zones, while the upper beach retained larger amounts of the deposited sediment as the profile adjusted. The shoreline growth slowed after the initial accretion, and the system shifted to reworking and redistribution.

Together, these results demonstrate that the sediment composition and coastal morphology of the Elwha delta evolved together as the shoreline transitioned from coarse-dominated to sand-dominated. This study also shows the value of tracking sediment fractions alongside morphological changes. Changes in the relative proportion of sand and coarse sediment helped identify patterns of sediment redistribution and storage across the delta following dam removal.

More broadly, this study demonstrates the potential of machine learning-based image segmentation for long-term coastal monitoring. By applying an automated classification workflow to thousands of shoreline images collected over more than a decade, sediment composition could be quantified at spatial and temporal scales that would be difficult to achieve using traditional field methods alone. This approach provides a new way to examine how sediment composition and coastal morphology evolve together following large sediment

disturbances such as dam removal.

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