

Early Geomorphic Adjustment Following Living Shoreline Installation Using Uncertainty-Aware sUAS Remote Sensing

By

Brendan Burchi

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Director of Thesis: Dr. Hannah Sirianni

Major Department: Earth, Environment, and Planning

ABSTRACT

Salt marshes and adjacent sediment flats are connected coastal environments whose spatial configuration regulates sediment transport, habitat quality, and shoreline stability. These low-relief environments are exposed to a range of physical processes that drive degradation, reducing productivity and limiting ecosystem services. Historically, shoreline stabilization has relied on hardening approaches, but recently nature-based solutions like engineered living shorelines have been increasingly used to promote shoreline stability and maintain ecological function.

Evaluating geomorphic responses to these installations requires monitoring frameworks capable of resolving fine-scale, variable change across the marsh-intertidal-nearshore gradient. At the Theodore Roosevelt Natural Area located on Bogue Banks barrier island, a Natrx ExoForms™ oyster breakwater was installed in late 2024. This study uses established small uncrewed aerial systems (sUAS)-based field and structure-from-motion Multiview stereo (SfM-MVS) methods to generate repeat pre- and post-installation topographic products capable of quantifying early shoreline and intertidal surface change. Multiscale model-to-model cloud comparison precision maps (M3C2-PM) were used to detect fine-scale geomorphic change at the 95% confidence interval, and DEMs of Difference filtered using the 95% linear error (DoD-LE95%) were used as

a raster-based comparison method. Results showed early-stage geomorphic adjustment across the study period, with the largest net lowering and sediment redistribution occurring between the baseline and first post-installation surveys. Across all survey periods, M3C2-PM detected a greater area of statistically significant change than DoD-LE95%, reflecting its ability to incorporate spatially variable point-cloud precision and detect fine-scale geomorphic adjustments that may be reduced or smoothed during raster-based differencing. These results show that early post-installation change was spatially variable and included localized lowering and accretion, emphasizing that short-term adjustment should not be interpreted as long-term living shoreline performance and demonstrating the value of repeat sUAS-SfM surveys with uncertainty-aware change detection in low-relief coastal settings.

Early Geomorphic Adjustment Following Living Shoreline Installation Using Uncertainty-Aware sUAS Remote Sensing

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By

Brendan Burchi

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Director of Thesis: Hannah Sirianni, PhD
Thesis Committee Members:
Rachel Gittman, PhD
Andrea Presotto, PhD

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CHAPTER ONE: INTRODUCTION

1.1 Background and significance

Coastal marsh-intertidal-nearshore systems form communities that are physically and ecologically connected, which thereby maintains their overall health (Shepard et al., 2011). Small changes in elevation, inundation, and habitat edge position can have large impacts on ecosystem function (Stragg & Mendelssohn, 2010; Fagherazzi et al., 2013; Thorne et al., 2014; Redelstein et al., 2018). Salt marsh and seagrass beds are particularly interdependent. Marsh vegetation influences sediment supply and hydrodynamics, while adjacent seagrass beds stabilize sediments and enhance water quality (Fonseca & Cahalan, 1992; Gacia & Duarte, 2001; Orth et al., 2016). These habitats often occur along narrow elevation gradients, making them highly sensitive to physical processes like sea-level rise, wave energy, and erosion (Möller et al., 2014). Centimeter-scale shifts in microtopography can alter inundation patterns, vegetation zonation, and sediment trapping efficiency (Kirwan & Megonigal, 2013), ultimately affecting marsh stability and nearshore habitat configuration.

As erosion intensifies, coastal armoring continues to increase in the United States and globally (Griggs, 2005; Gittman et al., 2015; Dugan et al., 2018; Theuerkauf et al., 2025) altering sediment pathways and reducing ecological connectivity. Nearly 14% (22,842 km) of the continental United States is hardened, most occurring along the Atlantic and Pacific sheltered shorelines (Gittman et al., 2015). Traditional hardened shoreline structures remain much more widespread in North Carolina than sill-based living shoreline structures (Polk & Eulie, 2018). More than 11.5% of total estuarine shoreline is permanent hardened shorelines, whereas only 8 km were classified as sills (Polk & Eulie, 2018). Living shorelines (e.g., oyster breakwater), including sill-based designs, are engineered nature-based shoreline stabilization approaches that

aim to preserve shoreline function while enhancing ecosystem services (Currin et al., 2009; Bilkovic & Mitchell, 2017; Smith et al., 2018). Because these installations are often placed adjacent to marsh edges, nearshore seagrass, and intertidal sand flats with a connected coastal system sensitive to centimeter-scale topographic variation, evaluating living shoreline performance requires monitoring techniques capable of resolving fine-scale, spatially continuous change across the marsh-intertidal-nearshore system.

Small-uncrewed aerial systems (hereinafter sUAS) provide an efficient means to map these environments simultaneously. sUAS-based high-resolution imagery and structure-from-motion Multiview stereo (SfM-MVS) photogrammetry enable centimeter-scale reconstruction of shoreline and structure position, habitat edges, and elevation surfaces (Pettyjohn et al., 2025). These capabilities are essential for detecting geomorphic responses to living shoreline installation, including marsh-edge movement, sediment redistribution, and nearshore habitat configuration. However, detecting subtle geomorphic change across low-relief marsh, intertidal, and shallow nearshore environments with living shorelines remains difficult because observed elevation change may be similar in magnitude to measurement uncertainty (Geesin et al., 2025; Pettyjohn et al., 2025; Pettyjohn, 2025).

1.2 Previous efforts in sUAS monitoring of living shorelines

Remote sensing platforms used to map shorelines and seagrass vary widely in spatial, spectral, and temporal resolution of the data they provide (Casella et al., 2016; Chabot et al., 2018; Román et al., 2021). Among these, sUAS platforms have become increasingly valuable because they can be deployed rapidly, capture fine-scale topography, and generate both 2D and 3D products suitable for geomorphic and habitat-change analysis. Recent living shoreline studies have used sUAS data in different ways. For example, Barry et al. (2025) used repeat annual RGB

orthomosaics to track vegetation development through time, whereas Geesin et al. (2025) used RTK-GNSS-controlled sUAS-SfM products to quantify horizontal marsh-edge retreat and vertical volumetric change using DEMs of Difference and uncertainty thresholds. Using sUAS, Pettyjohn et al., (2025) showed that shoreline behavior is strongly seasonal and hybrid living shorelines undergo rapid geomorphic adjustments following installation. These findings highlight the importance of repeated surveys across contrasting seasons and restoration phases to gain a better understanding of the system, as lower-frequency monitoring may miss important short-term geomorphic adjustments.

Despite growing applications of sUAS to monitor marsh-edge and shoreline dynamics, fewer studies have extended these analyses across adjacent shallow nearshore environments, including areas influenced by seagrass (e.g., Gittman et al., 2016; Palinkas et al., 2023). Yet living shorelines often affect a connected marsh–intertidal–nearshore system, where evaluating geomorphic response across the full gradient requires surveys that extend from exposed marsh edge surfaces into shallow water. Doing so introduces additional challenges, as water clarity, glint, and depth reduce sUAS image quality and SfM-MVS reconstruction (Sturdivant et al., 2017; Agrafiotis et al., 2018; Le Mauff et al., 2018). High-resolution sUAS-SfM workflows can generate spatially continuous products suitable for coastal monitoring (e.g., Hugenholtz et al., 2013). In low-relief environments, uncertainty-aware frameworks are needed to distinguish true geomorphic change from measurement noise when subtle elevation changes are of interest (e.g., James et al., 2017). Pettyjohn (2025) demonstrated the value of seasonally structured, uncertainty-aware sUAS-SfM monitoring for evaluating geomorphic response at a living shoreline site using Monte Carlo precision estimation and multiscale model-to-model cloud comparison precision maps (M3C2-PM) change detection techniques. The M3C2-PM technique

(James et al., 2017) builds on the original M3C2 workflow (Lague et al., 2013), which measures 3D change between point clouds by incorporating spatially variable measurement uncertainty from the photogrammetric process, making it suitable for SfM-derived data. Building on that foundation, this thesis examines how a raster-based DEM of Difference (DoD) workflow (Wheaton et al., 2010), which detects vertical change by subtracting two spatially aligned digital elevation models (DEMs), to evaluate which method reliably captures geomorphic change across a newly established living shoreline system.

1.3 Objectives

The objective of this thesis is to develop and apply an uncertainty-aware sUAS remote sensing framework for monitoring a living shoreline system using integrated 2D and 3D geospatial products. To achieve this, the study first establishes and validates high-accuracy sUAS-SfM datasets through RTK-GNSS control, photogrammetric quality assessment, and georeferencing validation. These surveys were intentionally designed to produce a multiuse coastal dataset capable of supporting future ecological and habitat-based applications; however, the focus of this thesis is specifically on geomorphic analysis. The central analytical objective is to quantify statistically significant surface and elevation change across marsh-edge and intertidal nearshore environments using uncertainty-aware change detection methods.

The specific objectives are to:

1. Generate and validate high-accuracy orthomosaics, dense point clouds, and DEMs for repeated coastal monitoring using sUAS-SfM-MVS.
2. Quantify statistically significant geomorphic change using uncertainty-aware point-cloud-based analysis.

CHAPTER TWO: STUDY AREA

2.1 Physical setting

The Theodore Roosevelt Natural Area (TRNA) is a 120-ha nature reserve located on Bogue Banks, North Carolina (Fig. 1 a, b), separating the Atlantic Ocean from the Bogue Sound. Bogue Banks is part of a chain of barrier islands located along the Crystal Coast that is highly urbanized, limiting space for ecosystems to adapt as physical processes like wave energy and tidal ranges influence geomorphic change (Doody, 2004; Pontee, 2013). On Bogue Banks, the exposed sound-facing shoreline is composed of loose sediment that undergoes significant change during high-energy storms like hurricanes or tropical storms (Sallenger, 2000). The estuarine shoreline is more sheltered (Pilkey et al., 2009) and marsh backed. Geomorphic variability results from hydrodynamic conditions controlled by waves and tidal flows (Fagherazzi et al., 2020; Mariotti & Fagherazzi, 2013; Leonardi et al., 2016, Ganju et al., 2017). Erosion occurs under moderate to frequent wind conditions (10 to 40 km/h) influencing wave power, with high-energy storm events with greater wind speeds (65 + km/hr) accounting for less than 1% of erosion (Leonardi et al., 2016). Gradual sea-level rise intensifies wave impacts, particularly during high tide as tidal ranges fluctuate (Mariotti & Fagherazzi, 2013). Sea-level is rising faster in North Carolina than in other parts of the North Atlantic (Zhang et al., 2024) at a rate of 0.0036 m/yr (NOAA Tides & Currents, 2024). Estuarine shorelines—like on the Bogue Banks—are vulnerable to sediment loss since there are no sandy beaches and foredunes that supply the shoreline with accumulated sediment from the backshore (Timmons et al., 2010). Although long-term trends indicate erosion, physical processes like waves, tides, and sea-level rise can also increase sediment accumulation (Ladd et al., 2019), leading to positive geomorphic and

biological responses, including elevation gain and marsh expansion (Kirwan & Megonigal, 2013; Seymour et al., 2019).

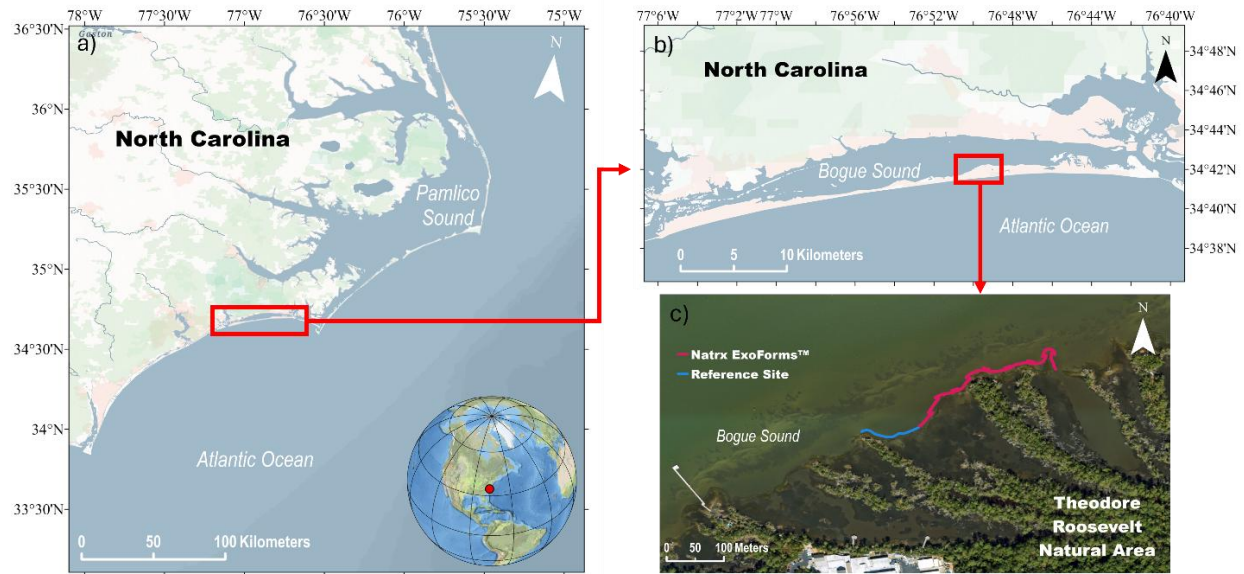


Figure 1. Global and regional scales of study site location (a). The red box shows Bogue Banks barrier island's location in coastal North Carolina. The Theodore Roosevelt Natural Area is a small area within the town of Pine Knoll Shores on the barrier island bordering the Bogue Sound (b). RGB aerial image obtained from USGS EarthExplorer (<https://earthexplorer.usgs.gov/>; accessed 2 February 2026) collected from the NAIP Program indicating the survey area with the position of the oyster breakwater Natrx ExoForms™ with adjacent reference site, and the North Carolina Aquarium at Pine Knoll Shores (c).

2.2 Ecological setting

Within the study site at the TRNA, several habitats create a productive but threatened ecosystem. The low marsh dominates most of the landscape. It is comprised primarily by smooth cordgrass (*Sporobolus alterniflorus*, formerly known as *Spartina alterniflora*) which grows stiff stems and a dense root network that reduces water flow and retains sediment (Mudd et al., 2010). Fringing seagrass eelgrass (*Zostera marina*), shoalgrass (*Halodule wrightii*), and widgeon grass (*Ruppia maritima*) are found in sand flats throughout North Carolina's estuaries (Fonseca et al., 1998; Hovel et al., 2002) creating patchy and continuous beds that support fish and small invertebrates (APNEP, 2022), sequester carbon, and improve water quality (Nellemann & Corcoran, 2009; Orth et al., 2010; Barnette, 2001; Landry & Golden, 2018; Gurbisz et al., 2016).

The eastern oyster (*Crassostrea virginica*) are abundant throughout the intertidal zone, where their reef structures dissipate wave energy and provide valuable services, including shoreline protection and shoreline stabilization (Scyphers et al., 2011; Tso et al., 2026). Understanding how the spatial configuration of marsh, seagrass, and oysters interact across the site is important when evaluating ecosystem and geomorphic change associated with shoreline stabilization.

2.3 Restoration efforts

Living shoreline restoration efforts exist on the TRNA shoreline in Bogue Sound. During the Fall of 2024 from October 16th – November 14th, the North Carolina Coastal Federation and project partners installed a total of 345 m of Natrx ExoFormsTM oyster breakwaters throughout the intertidal zone along the shoreline, making it one of the longest living shorelines in North Carolina. This study's geomorphic analysis focuses on roughly 345 m of Natrx ExoFormsTM living shoreline and 90 m reference site used to determine adjacent effects (see Fig. 1c). Designed to grow through oyster settlement overtime (Risinger, 2012), the living shoreline substrate were methodically placed mimicking natural shoreline configuration. Small gaps throughout each living shoreline design were intentional, but no natural shoreline landward of the oyster breakwaters is exposed due to the gaps being strategically placed with overlap (Fig. 2b). This allows wave and current energy associated with tides and moderate wave conditions to dissipate before reaching the natural shoreline but still promotes species connectivity between the landscape and the seascape. Because of the erosive nature and length of the TRNA shoreline, it is an ideal location to examine the stabilization potential of living shoreline substrates and how they impact marsh-back barrier island shoreline behavior being exposed to similar environmental conditions.



Figure 2. Aerial photo collected at 75 m from sUAS of TRNA Shoreline, Bogue Banks Barrier Island, Bogue Sound, and Atlantic Ocean (a). Example of Natrx ExoForms™ shoreline configuration and gap design captured from sUAS imagery (b) and structure design from ground image.

CHAPTER THREE: METHODOLOGY

3.1 sUAS Survey overview

To address Objective 1, high-accuracy 2D and 3D SfM-MVS products were developed and validated using Real-Time Kinematic Global Navigation Satellite Systems (RTK-GNSS) control, photogrammetric processing, marker-based georeferencing, and Monte Carlo accuracy assessment. In this study, sUAS surveys were conducted biannually at predicted low tides (NOAA Station ID: 8658467; Spooners Creek, NC) on days without precipitation, low winds (i.e., < 10 kts), and minimal wave energy (i.e., seas < 1 ft). Baseline surveys occurred in the Fall of 2024, which was closely followed by shoreline stabilization from October 16th – November 14th, 2024. Post-installation surveys occurred on April 27th, 2025, and November 14th, 2025 (Fig. 3).

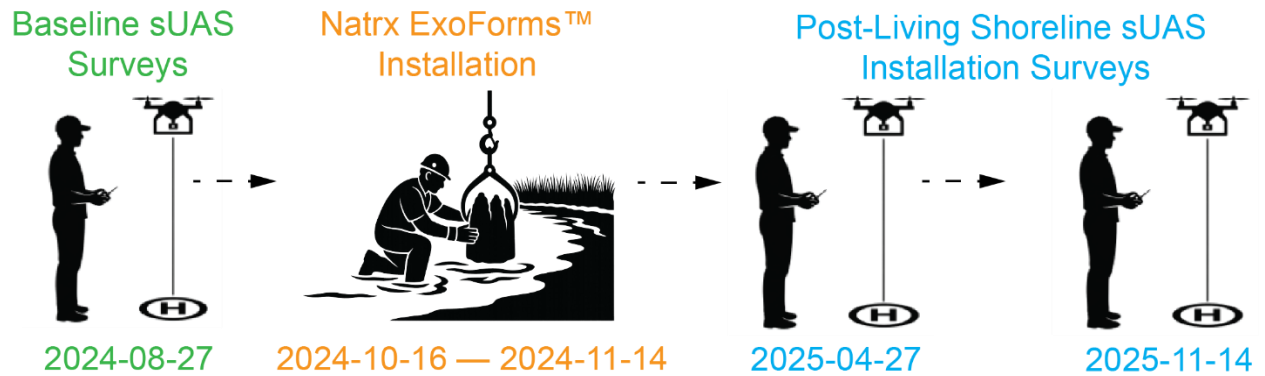


Figure 3. Survey timeline including installation period of Natrx ExoForms™ living shoreline substrate.

3.1.1 RTK-GNSS data collection

Ground control points (GCPs) and elevated GCPs (eGCPs), also referred to as markers, were placed throughout the study area to support SfM-MVS 3D network geometry and georeferencing. GCPs were used primarily to enhance topographic reconstruction of exposed bare-earth surfaces, whereas eGCPs were used to improve orthomosaic accuracy in vegetated

and nearshore environments where ground-level targets may not remain visible (Fig. 4). GCPs consisted of 0.25 m x 0.25 m black-and-orange targets, placed level with the ground and secured with survey-grade nails, for horizontal and vertical reconstruction of exposed surfaces. EGCPs consisted of circular black-and-orange and square black-and-white targets fixed atop PVC pipes of varying heights to maintain visibility above the marsh vegetation and shallow water during low tide. Roughly 50 GCPs and 25 eGCPs were placed for each survey.

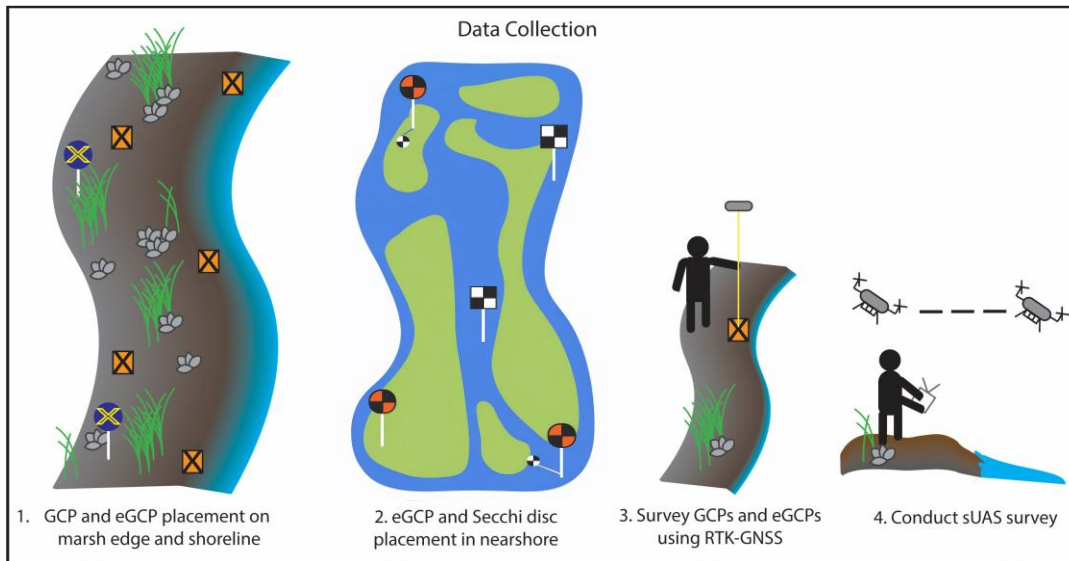


Figure 4. Data collection workflow throughout the marsh, shoreline, and nearshore environments during sUAS field surveys.

RTK-GNSS data were collected to obtain the spatial positions of markers using a Trimble Spectra Precision SP80 system with a reported high-precision static post-processed precision of 3 mm in the horizontal and 3.5 mm in the vertical (Root Mean Square Error (RMSE)) (Trimble Inc., 2019). GCPs were averaged over 30 epochs, while eGCPs were averaged over 3 epochs. Permanent reference stations operated by the North Carolina Geodetic Survey Continuously Operating Reference Station system (NC-CORS) network provided RTK-GNSS-based corrections. Two reference stations were utilized for this study. The closest reference station, “NCBE” located in Beaufort, NC was used for the baseline surveys; however, it is no longer

operational thus the next closest reference station “CALO” located in Harkers Island, NC (<https://ncgs.state.nc.us/pages/CORS-and-GNSS.htm>) was used for corrections for the post-living shoreline installation surveys.

All markers were evaluated for measurement reliability based on their spatial accuracy, the number of satellites, and the positional dilution of precision (PDOP). Across all surveys, the minimum number of satellites for a marker used in SfM-MVS processing was 10, with all markers having a PDOP value of 1.0 or below, indicating strong precision. NOAA’s Online Positioning User System (OPUS; <https://www.ngs.noaa.gov/OPUS/>) was used to derive reference station accuracy using peak-to-peak errors, a metric evaluating how much the reference station’s coordinates vary over time. Peak-to-peak errors were compounded with the RTK-GNSS survey accuracies in this study to calculate overall horizontal and vertical uncertainty used in SfM-MVS processing.

3.1.2 sUAS data collection

Aerial imagery was acquired using two sUAS platforms: the Phantom 4 Pro V2.0 and DJI Mavic 3M. The Phantom 4 Pro V2.0 was used for baseline surveys, while the Mavic 3M was used for post-installation monitoring. Survey design was intended to support both high-resolution topographic reconstruction and orthomosaic generation within limited tidal and wind windows. Sensor specifications for both platforms are summarized in Table 1.

Table 1. Specifications of the sUAS platforms used for image acquisition.

Platform	Sensor type	Spectral bands	Resolution	Additional features
DJI Phantom 4 Pro V2.0	1-inch CMOS RGB camera	Red, Green, Blue	20 MP	Global shutter
DJI Mavic 3M	4/3 CMOS RGB camera + multispectral array	Green (560 ± 16 nm), Red (650 ± 16 nm), Red-edge (730 ± 16 nm), Near-infrared (860 ± 26 nm)	RGB: 20 MP; Multispectral: 5 MP each	Integrated sunlight sensor

Baseline surveys were conducted using the DJI Phantom 4 Pro V2.0. Predetermined flight parameters were set in the Pix4D Capture Pro (v1.4.1) application (Pix4D, 2024). The flight height was set to 25 m, and front- and side-image overlap were 75% for all flights, providing a low ground sampling distance (GSD) of 0.73 cm/pixel. A crosshatch flight was conducted using a 70-degree gimbal pitch along the shoreline to enhance the topographic detail for 3D point cloud generation and elevation model reconstruction, following the oblique-imagery recommendation of James and Robson (2014) and James et al., (2017). However, these studies were developed to capture complex topography. During post-living shoreline installation surveys, imagery was captured using a DJI Mavic 3M utilizing a 70-degree gimbal pitch at 25 m (0.72 cm/pixel GSD) parallel to the shoreline, and 90-degrees at 35 m (1.62 cm/pixel GSD) perpendicular to the shoreline to provide multiple viewpoints for elevation reconstruction and to serve broader, multiuse survey needs. The remaining flight parameters (e.g., front/side overlap) remained the same as the baseline flights.

The sUAS imagery captured the living shoreline structures and adjacent marsh—intertidal—nearshore habitats, including the marsh edge, exposed and submerged sand and

mudflat, and seagrass, extending approximately 50 m seaward and 30 m landward of the shoreline. Total sUAS flight time for each field campaign was approximately 45 minutes. ISO, shutter speed, and exposure were set to automatic while imagery was captured along the flight path at 2-second intervals.

3.2 Structure-from-Motion Multi-View Stereo (SfM-MVS) data processing

3.2.1 Image import, alignment, and sparse cloud generation

All survey data collected from sUAS and RTK-GNSS were imported into Agisoft Metashape (v2.0.3, v2.1.2) for SfM-MVS photogrammetric processing as different projects using a single-channel dataset. Image alignment, sparse point cloud generation, and dense cloud reconstruction followed a standard workflow. SfM-MVS processing parameters used in Agisoft Metashape are summarized in Table 2.

Table 2. Agisoft Metashape processing parameters used in the SfM-MVS workflows.

Step	Parameter	Value
Image quality screening	RGB threshold	0.7
Alignment	Accuracy	Highest
Alignment	Key point limit	50,000
Alignment	Tie point limit	5,000
Sparse cloud refinement	Reprojection error threshold	0.5
Monte Carlo	Marker withholding	30%
Monte Carlo	Iterations	100
Dense cloud generation	Quality	High
Dense cloud generation	Depth filtering	Mild

Established sUAS-SfM workflow approaches and best practices described by Cooper et al., (2021), Guan et al., (2022), and Pettyjohn et al., (2025) were followed to derive accurate 3D point clouds, DEMs and orthomosaic images from the sUAS imagery. Image quality was estimated before alignment, and low-quality images were disabled based on the thresholds specific to RGB datasets (see Table 2). Image alignment was then performed using standardized SfM-MVS settings in Agisoft Metashape. Stationary tie points were excluded from alignment parameters to eliminate artifacts caused by the camera sensor or lens, so that image alignment relied on the real surface geometry rather than static tie point artifacts (Agisoft LLC, 2023). This process generated a sparse point cloud (e.g., tie point cloud) representing the initial 3D structure of the environment. Images that did not align because of a lack of distinct features, such as open water or uniform benthic texture across overlapping imagery, were disabled.

Aligned images were then assessed using reprojection error, which quantifies the pixel residual between observed tie point locations and the estimated image positions based on the photogrammetric network geometry. Reprojection errors were assessed in both RStudio (v.12.1) and Agisoft Metashape. Image outliers were disabled, followed by image realignment and sparse point cloud reconstruction. Points with reprojection errors greater than 0.5 pixels were removed across all projects except the baseline survey (2024/08/27), for which a threshold of 0.4 pixels was applied, following the gradual-selection error-reduction approach outlined in Over et al., (2021). The baseline survey was captured prior to oyster breakwater installation when the site was dominated by low-texture, smooth substrate. Feature detection and matching in SfM workflows are less reliable on such surfaces (Westoby et al., 2012), which can result in a sparse tie point network with higher pixel errors. Applying the 0.4 pixel threshold retained a greater portion of these tie points relative to the 0.5 pixel threshold used across other surveys.

3.2.2 Camera optimization parameters

Bundle adjustments were performed using the Optimize Cameras feature in Agisoft Metashape throughout the photogrammetric workflow. Camera optimization evaluates image residuals in pixel units, refines camera orientation parameters, and improves triangulation of tie point coordinates (Agisoft LLC, 2023). Initial bundle adjustments refine image network geometry and minimize residuals in 3D pixels, improving the sparse point cloud geometry and overall accuracy prior to georeferencing to evaluate errors in pixels (Westoby et al., 2012; James et al., 2017). After georeferencing, RMSE values were reported in meters. Camera model parameters were tested to assess the camera network geometry and performance to derive the lowest RMSE (m) post-georeferencing across all datasets (Cooper et al., 2021; James et al., 2017). Excess calibration (e.g., over-parametrization) can result in smooth and systemically distorted surface models, particularly in sUAS imagery (James & Robson, 2014; James et al., 2017). Four models, tested on all five topographic surveys, ran a combination of general and advanced parameters to determine the optimal camera alignment (Table 3). Two of the models included adaptive camera model fitting- an advanced parameter that automatically selects a set of refined camera calibration parameters by evaluating their reliability and limiting adjustments, strengthening image geometry and sparse point cloud generation (Agisoft LLC, 2023).

Table 3. Bundle adjustment parameters using “Optimize Camera” tool in Agisoft Metashape.

Model	Camera Parameters
A	f, cx, cy, k1-k3
B	f, cx, cy, k1-k3, adaptive camera model fitting
C	f, cx, cy, k1-k3, p1, p2
D	f, cx, cy, k1-k3, p1, p2 adaptive camera model fitting

Bundle adjustment camera models A and C tested camera network geometry without adaptive camera model fitting. Camera model A optimized focal length (f), principal point (cx , cy), radial distortion coefficients ($k1$, $k2$, $k3$), and camera model C added tangential distortions

($p1$, $p2$). Camera models B and D followed the same general parameters as A and C but included adaptive camera modeling fitting enabled. After 100 Monte Carlo simulations, models B and D resulted in the same control and checkpoint errors lower than models A and C, indicating improved model performance when adaptive camera model fitting is used. For this study, camera model D was used as the more complete camera model even though its performance did not differ from model B in this comparison.

3.2.3 Marker integration and georeferencing

Marker integration and georeferencing formed the foundation of the SfM-MVS workflow by tying each model to RTK-GNSS control and defining the survey-specific uncertainty used in later accuracy assessment. Here, GCPs and eGCPs were visually identified in individual images and manually placed in each RGB chunk prior to importing RTK-GNSS positional data. Marker accuracy values in meters were introduced by replacing the default marker accuracy setting (0.005) in the project reference settings with survey-specific measurement errors derived from the RTK-GNSS and NC-CORS network using equations 1 and 2.

Equation 1: Horizontal uncertainty = $\sqrt{m^2 + Lat^2 + Long^2}$

Equation 2: Vertical uncertainty = $\sqrt{m^2 + OH^2}$

Horizontal uncertainty incorporated the XY rover errors recorded for each survey point by the RTK-GNSS (m^2 ; equation 1), together with the latitude and longitude peak-to-peak errors derived from the OPUS solution (Lat^2 and $Long^2$; equation 1). Vertical uncertainty incorporated the Z rover errors from the RTK-GNSS (m^2 ; equation 2) together with orthometric height peak-to-peak error from the OPUS solution (OH^2 ; equation 2). Horizontal and vertical RTK-GNSS coordinates were then applied to the GCPs and eGCPs, projecting the photogrammetric model to NAD83 (2011) / North Carolina (EPSG: 6542). GCP and eGCP residual errors were assessed

in meters, and markers containing high reprojection errors were disabled to reduce overall uncertainty while maintain sufficient model constraint and balanced spatial distribution. Marker and tie point errors (in pixels) were also adjusted from Agisoft’s default values of 0.5 and 1.0, respectively, in conjunction with the RTK-GNSS-derived survey errors to reflect survey-specific uncertainty. The combined uncertainty from these error sources was then used in Monte Carlo simulations.

3.2.4 Monte Carlo accuracy assessment

To obtain a more robust estimate of spatial accuracy than a single bundle adjustment or one checkpoint configuration RMSE can provide, georeferencing uncertainty was assessed through repeated Monte Carlo simulations in Agisoft Metashape using a Python script adapted from James et al., (2017). Here, Monte Carlo simulation refers to repeated random partitioning of markers into control and checkpoint sets to quantify how sensitive georeferencing accuracy is to marker configuration. For each simulation, 30% of markers were randomly chosen to be withheld acting as checkpoints during independent bundle adjustments, while the remaining 70% of GCPs and eGCPs generate the model (Cooper et al., 2021; Pettyjohn et al., 2025). A total of 100 simulations were performed for all surveys. Mean horizontal and vertical RMSE values from each simulation were then summarized using descriptive statistics (e.g., min, max, average) and used as final uncertainty measures. This approach reduces overfitting and minimizes bias associated with any single GCP/eGCP configuration; however, all markers were ultimately used to generate the final SfM-MVS data products following Pettyjohn et al. (2025).

3.2.5 Dense point cloud and DEM generation

Dense point cloud generation was a critical component of the workflow because the resulting point clouds supported both DEM construction and subsequent M3C2-PM change

detection analyses. After georeferencing and assessing 3D network accuracy, dense point clouds were built following high-quality and mild depth filtering. Depth filtering in Agisoft Metashape ranges from high to mild, controlling how strict outlying or noisy points are removed during dense cloud generation (Agisoft LLC, 2023). Mild depth filtering was selected for this study to avoid removing small-scale topographic detail that a more aggressive filter might remove. Using Agisoft’s “Classify Ground Points” tool, non-ground surface features, including vegetation and water-affected points, were classified and removed where possible. A max angle of 15 degrees was selected to reflect the low-relief, gently sloping nature of the intertidal study area. The max distance of 0.05 m was chosen to match the expected vertical scale of the intertidal surface, accounting for slight variations of non-bare ground features. A cell size of 5 m was used to differentiate between bare ground features and marsh vegetation (Agisoft LLC, 2023). Additional manual filtering was then performed to remove artifacts and points with high uncertainty, resulting in a quality-controlled ground-class point cloud for each survey. The bare-earth ground point clouds were used as the topographic-surface input for the M3C2-PM and to construct the uninterpolated DEMs used in the DoD analysis. A subsequent exposed-topography mask was applied to further reduce shallow-water influence in the change-detection outputs, as described in Section 3.3.3.

3.3 Geomorphic change detection

To address Objective 2, geomorphic change between successive surveys was quantified using uncertainty-aware ground point-cloud comparison, supplemented by DEM-based differencing and elevation profile analysis. M3C2-PM was used as the primary change-detection method because it propagates spatially variable SfM-MVS uncertainty directly within the point-cloud framework and is well suited for resolving subtle 3D change in low-relief living shoreline

projects (Pettyjohn, 2025). DoDs were also generated because DEM-based differencing remains a widely used and interpretable approach for quantifying elevation and volumetric change in living shoreline systems (e.g., Geesin et al., 2025). Applying both methods allowed comparison between a point-cloud-based uncertainty-aware workflow and a conventional raster-based workflow within the same living shoreline setting, while elevation profiles provided additional cross-shore context for interpreting localized patterns of erosion and accretion.

3.3.1 Shoreline sediment change derived from M3C2-PM (95% confidence)

M3C2-PM outputs were created using CloudCompare v2.12.4 (CloudCompare, 2024) based on parameter values selected through sensitivity testing of scale-based roughness analysis and point-density statistics (Table 4). A 1 m normal scale was selected because our trial-and-error analysis showed that surface roughness stabilizes at this radius, capturing dominate structure without over smoothing. The normal scale defines the radius of the sphere used to estimate the local surface normal at each core point in the point cloud, where larger values produce smoother normals that are more representative of the surface pattern but may miss fine-scale topographic detail. A 0.25 m projection scale defined the radius of the normal-aligned projection cylinder used to sample neighboring points from each input point cloud, while a 0.5 m cylinder half depth specified the maximum normal direction distance over which points were included to ensure sufficient point density support for stable distance estimates. A minimum neighbor threshold of 10 controlled the minimum number of points required within the projection cylinder for a distance to be computed to avoid unstable estimates from poorly supported neighborhoods. Only core points were only computed where both input point clouds had more than 10 neighbors within the projection cylinder were kept, reducing noise in areas of low point density. Spatially variable SfM-MVS precision was propagated into each distance estimate to compute 95%

confidence intervals, so that only statistically significant geomorphic change was interpreted (Table 4).

Table 4. M3C2-PM parameter values used for point-cloud change detection area between marsh edge and living shoreline.

Parameter	Symbol	Value	Selection basis	Source
Normal scale	D	1 m	Plateau in scale-dependent roughness analysis	Lague et al., 2013
Projection scale	d	0.25 m	Exceeds mean point spacing (~ 3 cm) while remaining smaller than microtopographic feature scale	Lague et al., 2013
Cylinder half-depth	—	0.5 m	Exceeds expected vertical variability of mudflat surface	Lague et al., 2013
Minimum neighbors	—	10	Maintains stable mean surface position ($< 5\%$ of expected cylinder support)	Lague et al., 2013
Core point spacing	—	0.10 m	Reduces computational cost while preserving spatial resolution	Lague et al., 2013
Precision map input	—	SfM-MVS precision estimates	Used to propagate uncertainty in M3C2-PM distance calculations	James et al., 2017

3.3.2 DoDs using 95% linear error

DEMs of Difference (DoDs) were generated for each survey period by subtracting the earlier DEM from the later DEM to quantify raster-based elevation change across the shoreline (Wheaton et al., 2010). Prior to differencing, DEMs were aligned to a common resolution and clipped to a consistent analysis mask. Vertical uncertainty for each DEM was derived from the mean of 100 Monte Carlo simulations. Survey-pair vertical uncertainty was multiplied by 1.96 to calculate the 95% linear error (LE95%) following NSSDA procedures (FGDC, 1998; Cooper et al., 2013). DoDs were filtered using LE95% as a single global threshold, so the resulting surface represented only elevation differences exceeding the combined uncertainty of both input DEMs. This procedure aims to reduce the likelihood of interpreting raster noise as geomorphic change.

3.3.3 Filtering exposed topography

Exposed intertidal topography was delineated from orthomosaic imagery in ArcGIS Pro v3.6.0 (ESRI, 2025) to further constrain change detection analyses to visibly interpretable sediment surfaces and reduce the influence of shallow water. This step was used as a secondary filter because shallow water could not be consistently removed during initial point-cloud or raster processing due to the complex, low-relief intertidal surface behind the living shoreline structures. Object-based image segmentation was performed using the Segment Mean Shift (Image Analyst toolbox). The tool groups spectrally and spatially similar pixels into groups based on defined spectral detail, spatial detail, and minimum segment size parameters, which were set to 20, 10, and 250 in this study, respectively. The resulting segmented raster for each survey was converted to discrete vector polygons using the Raster to Polygon tool (Conversion toolbox). The polygons were then overlaid on the corresponding orthomosaic, and polygons representing exposed or visibly interpretable intertidal topography surfaces were manually identified and merged into a single mask layer representing the spatial extent of exposed topography at the time of each survey.

A unique exposed-topography mask was produced for each survey date using that survey's corresponding orthomosaic, as the spatial extent of exposed intertidal surface varied between each survey date due to differences in tidal stage, sediment redistribution, and surface cover at the time of each sUAS flight. This workflow was repeated for each survey date so that each change-detection period used the appropriate date-specific mask. The exposed-topography masks were applied to the M3C2-PM and DoD-LE95% change-detection outputs to restrict analysis to visibly interpretable intertidal topography and reduce areas affected by shallow water. For the DoD-LE95% rasters, masks were applied using the Extract by Mask tool in the Spatial

Analyst toolbox. For the M3C2-PM outputs, masks were applied using Clip (Analysis toolbox) on the significant change points before being gridded as a raster based off their original core point spacing.

3.3.4 Area and volumetric calculations

M3C2-PM significant area and volumetric change were calculated following the general workflow described in Bernard et al. (2021), using the exposed-topography-masked M3C2-PM core-point outputs described in Section 3.3.3. For each survey comparison, significant change was identified at M3C2-PM core points where the magnitude of the M3C2-PM distance exceeded the local 95% confidence interval. The 95% confidence interval is computed per-point by the M3C2-PM algorithm in CloudCompare v2.12.4 by combining local surface roughness, normal-direction uncertainty, and registration error. This interval is stored as a scalar field, giving each core point its own significance threshold for detecting meaningful change (Lague et al., 2013; James et al., 2017). Significant points with negative distances were classified as erosion, and significant points with positive distances were classified as accretion. Because the M3C2-PM output was not rasterized, each significant core point was assigned a representative area based on the spacing of the M3C2-PM core-point dataset. The mean Euclidean natural neighbor distance of the exposed topography-masked core points was 0.107 m across all survey comparisons, calculated using the Average Nearest Neighbor tool (Spatial Statistics toolbox). This value was computed from the masked core point feature class in ArcGIS Pro and represents the mean distance from each core point to its nearest neighboring core point across the study area, confirming that core point density was preserved through the masking step. This measured spacing closely aligns with the input 0.1 m core point spacing parameter used to derive the M3C2-PM in CloudCompare v2.12.4 (see Table 4). This spacing was squared to produce a per-

point area of 0.0114 m^2 . Significant erosion and accretion areas were calculated by multiplying the number of significant core points in each class by 0.0114 m^2 . This per-point area was held constant across all survey comparisons, as the mean nearest neighbor distance was consistent across all surveys. Volumetric change was calculated by multiplying each significant point's signed M3C2-PM distance by 0.0114 m^2 and summing values separately for erosion, accretion, and net change. Net volume change was computed as the total accretion volume minus total erosion volume, such that a positive net value indicates a gain in total sediment and a negative net value indicates a loss over the entire study area.

Prior to area and volumetric calculations, the significant DoD-LE95% change rasters were clipped to the survey date specific exposed topography masks described in section 3.3.3, restricting analysis to visible intertidal sediment surfaces. Using the survey-period specific LE95% global threshold, cells with elevation differences above (accretion) or below (erosion) the calculated value were assigned no data and excluded from area and volumetric calculations. Since the DEMs had a 0.05 m cell size, each raster represented 0.0025 m^2 . Significant erosion and accretion areas were calculated by multiplying the number of significant cells above or below the survey-period specific LE-95% global threshold in each class by 0.0025 m^2 . Volumetric change was then calculated by multiplying each significant cell's elevation difference by 0.0025 m^2 and summing values separately for erosion, accretion, and net change. Results were computed separately for each survey comparison period to allow temporal analysis of geomorphic change across the study area.

3.3.5 Elevation profile change

Two-dimensional elevation profiles were generated along predefined shoreline transects to characterize cross-shore topographic variation and support interpretation of point-cloud- and

DEM-derived change metrics. Profiles were extracted from each DEM across both survey sites, including 3 at each reference site and 3 landward of each living shoreline substrate. Because cross-shore elevation structure is a primary control on shoreline behavior and sediment transport processes (Castelle & Masselink, 2023), the profiles were used to identify localized erosion and accretion between the marsh edge and the living shoreline structures at low tide. Profiles were plotted for each survey interval to enable direct visual comparison of shoreline response through time.

CHAPTER FOUR: RESULTS

4.1 Results for Objective 1: Development and validation of SfM-MVS products

Objective 1 was critical because the reliability of Objective 2 depended on the accuracy, precision, and georeferencing stability of the SfM-MVS products used for change detection. Results related to Objective 1 are presented first and include survey acquisition, RTK-GNSS control quality, photogrammetric performance, and Monte Carlo-based georeferencing accuracy used to evaluate the reliability of the 2D and 3D sUAS-SfM products.

4.1.1. Data validation

Data validation incorporated three primary sources of uncertainty in the SfM-MVS workflow: 1) ground errors derived from the RTK-GNSS in meters, 2) reprojection error reported in pixels, and 3) marker accuracy reported in pixels. Together, these metrics characterize object-space georeferencing accuracy, image-space alignment quality, and marker placement precision within the photogrammetric network (James et al., 2017; Cooper et al., 2021; Guan et al., 2022).

4.1.2 RTK-GNSS network reliability

RTK-GNSS network reliability was evaluated first because these control measurements formed the georeferencing backbone for all SfM-MVS products; therefore, any positional instability at this stage would propagate directly into all downstream spatial products and change detection analyses. In this study, connecting RTK-GNSS to the NC-CORS network consistently yielded centimeter level horizontal and vertical rover errors (Table 5). Overall RMSE (m) network ranged from 0.013 – 0.015 indicating stable positional accuracy from the NC-CORS base station. Peak-to-peak errors demonstrate high control levels projecting the rover to NAD 83

/ North Carolina State Plane (EPSG: 6542) with X ranging from 0.002 – 0.007 (m), Y ranging from 0.001 – 0.007 (m), and Z ranging from 0.048 – 0.055 (m). Vertical accuracy is slightly larger, but still within the centimeter level. The NC-CORS geometric network separates horizontal accuracy into separate X and Y uncertainty values while the RTK-GNSS combines XY. Rover-reported errors (m) confirm that using the NC-CORS network supported reliable RTK-GNSS fixes when surveying GCPs and eGCPs. Horizontal (XY) accuracies, an average taken from the number of GCPs and eGCPs using in SfM-MVS processing vary in uncertainty from 0.007 to 0.015 (m). Vertical (Z) ranges from 0.008 to 0.017 (m). The peak-to-peak errors and rover errors were combined in this study using the sum in quadrature equation (equation 1, 2) to input overall horizontal and RMSE error values into Agisoft Metashape.

Table 5. Uncertainty measures from NC-CORS geometric network and RTK-GNSS rover errors used to calculate georeferencing accuracy.

Survey	Site	Overall RMSE (m)	Peak-to-peak errors (m)			Rover errors (m)		No. of GCPs/eGCPs
			X RMSE	Y RMSE	Z RMSE	XY RMSE	Z RMSE	
2024-08-27	Natrx	0.015	0.002	0.005	0.048	0.007	0.008	44
2025-04-27	Natrx	0.013	0.007	0.007	0.055	0.010	0.011	39
2025-11-14	Natrx	0.013	0.005	0.001	0.052	0.009	0.010	43

4.1.3 Photogrammetric and georeferencing accuracy

Photogrammetric and georeferencing accuracy were evaluated to confirm that each SfM-MVS model was both internally stable and externally well constrained, since errors at this stage would directly affect the positional reliability of the orthomosaics, dense point clouds, DEMs, and all subsequent change detection results. Photogrammetric and georeferencing accuracy metrics for all surveys are summarized in Table 6. Image-space accuracy was assessed using marker reprojection error and sparse cloud reprojection error. Marker reprojection error reflects how well manually placed GCP/eGCP observations fit the optimized model. Marker reprojection error was generally low, with only the November 14th, 2025, dataset exceeding 1.0 pixels (Table

6), indicating a higher difference between the photogrammetric model and marker positions. In contrast, sparse cloud reprojection error, which reflects how well tie points are reconstructed across the image network overall, exceeded 1.0 pixels in the April 27th, 2025, survey. This indicates a greater difference between observe and model predicted tie point positions across overlapping images. These elevated sparse cloud reprojection errors indicate reduced tie point consistency across portions of the image network, likely associated with open water, low-texture benthic surfaces, and other survey-specific image conditions that weaken image matching performance (Nocerino and Menna, 2020; Casella et al., 2024). The November 14th, 2025, survey returned a marker reprojection error of 1.251 pixels, the only survey to exceed the 1.0 pixel threshold, and should be noted as a potential source of elevated georeferencing uncertainty.

Table 6. Summary of photogrammetric and georeferencing accuracy metrics for all surveys. Image-space accuracy is reported as marker and sparse cloud reprojection error (pixels). Georeferencing accuracy is reported as horizontal and vertical RMSE (m) based on GCP/eGCP residuals.

Date	Site	Survey type	Image-space accuracy (pix)		Georeferencing accuracy (m)		No. of markers (n)
			Marker reprojection	Sparse cloud reprojection	Horizontal RMSE	Vertical RMSE	
2024-08-27	Natrx	Topographic	0.526	0.472	0.013	0.050	44
2025-04-27	Natrx	Topographic	0.655	1.230	0.019	0.056	39
2025-11-14	Natrx	Topographic	1.251	0.959	0.009	0.052	43

In this study, object-space georeferencing accuracy was reported as horizontal and vertical RMSE derived from GCP/eGCP residuals using the uncertainty equations described in the photogrammetric processing section (Equations 1 and 2). Horizontal RMSE remained low across all surveys (0.009 m to 0.019 m), while vertical RMSE for topographic surveys ranged from 0.050 m to 0.052 m (see Table 6). This difference indicates stronger horizontal than vertical georeferencing precision, which is expected in SfM-MVS workflows where vertical error propagation is typically more sensitive to control quality, image geometry, and surface reconstruction uncertainty (e.g., Pettyjohn et al., 2025). Although sparse cloud reprojection error

exceeded 1.0 pixels in several surveys, marker reprojection error and final GCP/eGCP-based RMSE remained comparatively consistent. This suggests that localized image-space mismatches within the sparse cloud did not propagate into substantial degradation of final georeferencing accuracy.

4.1.4 Monte Carlo georeferencing accuracy

Because georeferencing uncertainty directly influences confidence in subsequent change detection, model accuracy was further evaluated using a Monte Carlo marker-withholding framework that quantified error across repeated checkpoint configurations. Across all surveys, mean XY RMSE ranged from 0.016 m to 0.024 m, and mean Z RMSE ranged from 0.039 m to 0.070 m (Table 7). Vertical error was highest in the 08/27/2024 survey and decreased to 0.039 m by 11/14/2025, indicating improved vertical precision through time (Fig. 5). Standard deviation across the 100 Monte Carlo simulations remained low for both horizontal and vertical metrics, with XY SD ranging from 0.001 m to 0.002 m and Z SD ranging from 0.002 m to 0.003 m (Table 7). This limited spread indicates that georeferencing precision was stable across repeated marker-withholding simulations and was not strongly influenced by any single checkpoint configuration. Overall, mean Z RMSE remained higher than mean XY RMSE, which is consistent with the greater sensitivity of vertical accuracy to control uncertainty, image geometry, and SfM surface reconstruction.

Table 7. Summary statistics from 100 Monte Carlo simulations for each survey. Reported metrics include mean, standard deviation, median, minimum, and maximum horizontal (XY) and vertical (Z) georeferencing RMSE.

Survey	Type	XY mean (m)	XY SD (m)	XY med (m)	XY min (m)	XY max (m)	Z mean (m)	Z SD (m)	Z med (m)	Z min (m)	Z max (m)
2024-08-27	Topo	0.016	0.001	0.015	0.013	0.018	0.070	0.002	0.070	0.066	0.075
2025-04-27	Topo	0.021	0.001	0.017	0.014	0.020	0.050	0.002	0.051	0.039	0.054
2025-11-14	Topo	0.024	0.002	0.024	0.019	0.026	0.039	0.003	0.040	0.025	0.044

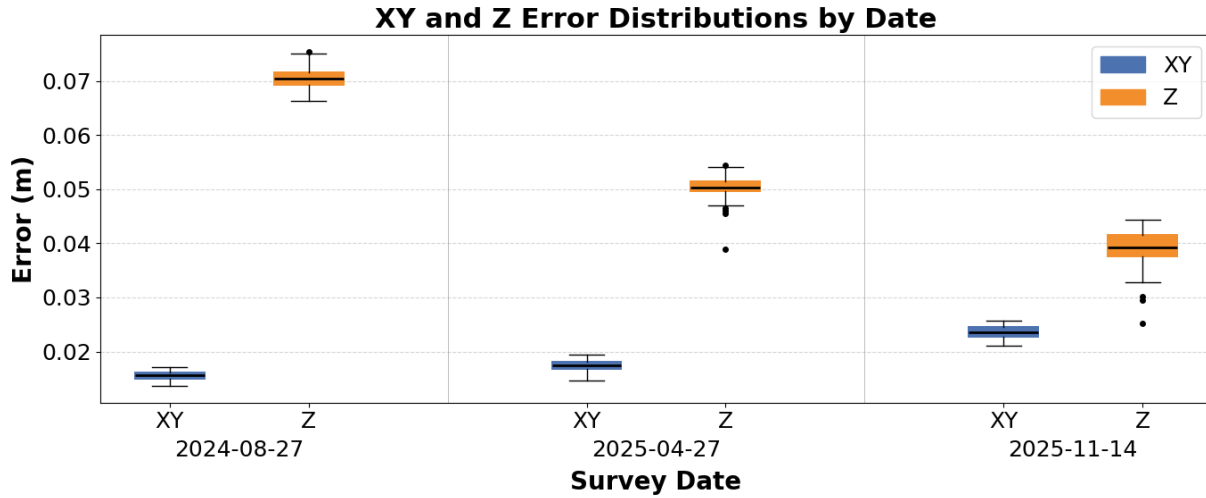


Figure 5. Topographic survey uncertainty using 100 Monte Carlo simulations accounting for bias and spatial variability in the georeferenced dataset.

The magnitude and variability of the Monte Carlo–derived RMSE values are consistent with recent SfM uncertainty assessments that apply marker-withholding approaches (e.g., Pettyjohn et al., 2025), where horizontal error typically remains at the centimeter scale and vertical error approaches decimeter-scale precision in coastal environments. The similarly low standard deviations observed across simulations in this study further indicate that georeferencing uncertainty is robust to checkpoint selection when control is well distributed. These results also fall within the broader range of georeferencing accuracies reported in earlier sUAS-based photogrammetric studies (e.g., Elsner et al., 2008), although more recent SfM workflows incorporating RTK-GNSS and uncertainty propagation provide a more direct methodological comparison (Pettyjohn et al., 2025).

4.2 Results for Objective 2: Geomorphic change assessment

Results related to Objective 2 are presented next and include M3C2-PM change detection, DEM-based DoDs, and elevation profile analyses used to quantify statistically

significant geomorphic change across survey periods at reference and living shoreline sites using the validated SfM-MVS products developed under Objective 1.

4.2.1 Natrx ExoForms™ exposed intertidal topography mask

Exposed intertidal topography varied spatially and temporally across survey dates, reflecting differences in wind direction and low tide levels at the time of each flight and the dynamic low-relief sediment surface behind the living shoreline structures. Figure 6 provides an example of the exposed-topography masking results for the August 27th, 2024, and April 27th, 2025, surveys. Both August 27th, 2024, and April 27th, 2025, surveys detected large areas of exposed topography throughout the study, particularly the reference shoreline and portions of the living shoreline (Fig. 6 a, b). The intersection of these two masks defined the shared exposed-topography area used for the August 27th, 2024 – April 27th, 2025, change-detection comparison (Fig. 6 c). This overlap area represents locations where surface elevations were visibly interpretable in both surveys and therefore provides the analysis extent for comparing M3C2-PM and DoD-LE95% change. Preliminary water levels from NOAA Tide Station 865657 (Spooners Creek, NC) show that the MLLW levels for each survey, August 27th, 2024, April 27th, 2025, and November 14th, 2025, were approximately 0.06 m, -0.07 m, and 0.04 m (NOAA Station ID: 8658467; Spooners Creek, NC) when the survey occurred. Winds were recorded as the daily mean from NOAA Station ID: BFTN7 – 8656438; Beaufort, NC. The baseline survey showed ideal conditions, with low winds (2.84 kts) from the Southwest direction (offshore). Winds then switched to the Northwest and North direction (onshore), staying below 10 knots (kt). The highest wind speed during a survey was on April 27th, 2025, when the wind was onshore at 8.32 kt, however, the water level being -0.07 m was low enough that the intertidal shoreline topography was significantly exposed (Table 8).

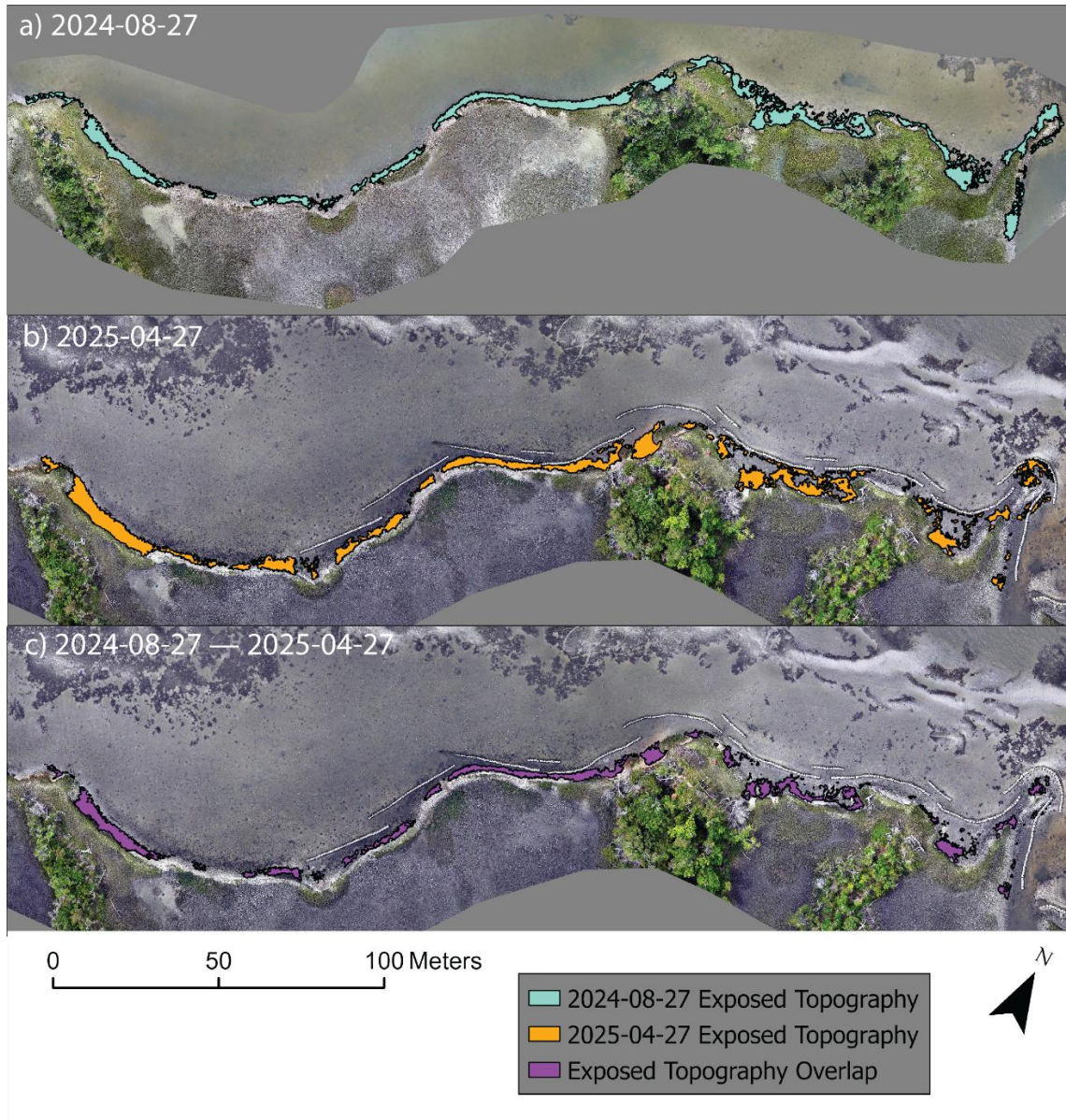


Figure 6. Three-panel example of the surface-condition masking workflow. Panels show the August 27th, 2024, orthomosaic and mask, the April 27th, 2025, orthomosaic and mask, and the final exposed-overlap area used for paired change detection. Quantitative change detection was restricted to areas as exposed topography in both surveys

Table 8. Environmental conditions reported during sUAS flights. Pix4D Capture Pro was used for baseline surveys. Predicted MLLW Station ID: 8658467; Spooners Creek, NC. Mean Wind Station ID: BFTN7 – 865643; Beaufort, NC)

Date	Survey Site	Control Software	Predicted MLLW (m)	Mean Wind (kt)	Mean Humidity (%)	Monte Carlo Mean XY RMSE (m)	Monte Carlo Mean Z RMSE (m)
2024-08-27	NatrX	PIX4DCapture Pro	0.06	SW 2.84	62	0.016	0.070
2025-04-27	NatrX	DJI Pro 2	-0.07	NW 8.32	48	0.021	0.050
2025-11-14	NatrX	DJI Pro 2	0.04	N 3.32	56	0.024	0.039

4.2.2 *Natrx ExoForms™ M3C2-PM and DoD-LE95% comparisons*

Across all Natrx ExoForms™ survey intervals, both the M3C2-PM and DoD-LE95% mapped net lowering as the dominant short-term surface-change pattern, although the spatial extent and magnitude of mapped change differed between methods (Fig. 7; Table 9). The M3C2-PM compares point clouds using local 3D distances with a per-point significance threshold. The DoD-LE95% compares raster elevations using a single global vertical uncertainty threshold derived from DEM vertical accuracy. As a result, M3C2-PM may identify a broader spatial extent of significant change than DoD-LE95%, particularly in low-relief environments where elevation differences are small relative to the global uncertainty threshold. Each survey interval was analyzed using the exposed-topography overlap for the two surveys being compared. During the August 27th, 2024 – April 27th, 2025, interval (Fig 7. a, b), both methods identified significant erosion through the central portion of the site, with smaller areas of accretion near the reference area and along the landward margin. However, M3C2-PM (Fig. 7 a) mapped a broader and more spatially continuous erosional band than the DoD-LE95% (Fig. 7 b). During the April 27th, 2025 – November 14th, 2025, period (Fig. 7 c, d), M3C2-PM mapped relatively limited and patchy significant change (Fig. 7 c), whereas DoD-LE95% (Fig. 7 d) mapped a more restricted pattern dominated by erosional change. Previous areas that were accretionary at the reference site in the northeast corner of the map were erosive during this interval. Volumetric summaries further show differences between the two change detection methods (Table 9). For August 27th, 2024 – April 27th, 2025, the M3C2-PM identified more significant change area (256.11 m² versus 7.53 m²), more accretion (8.56 m³ versus 0.31 m³), and more erosion (-18.71 m³ versus -1.04 m³) driving a greater overall net volumetric change than the DoD-LE95%.

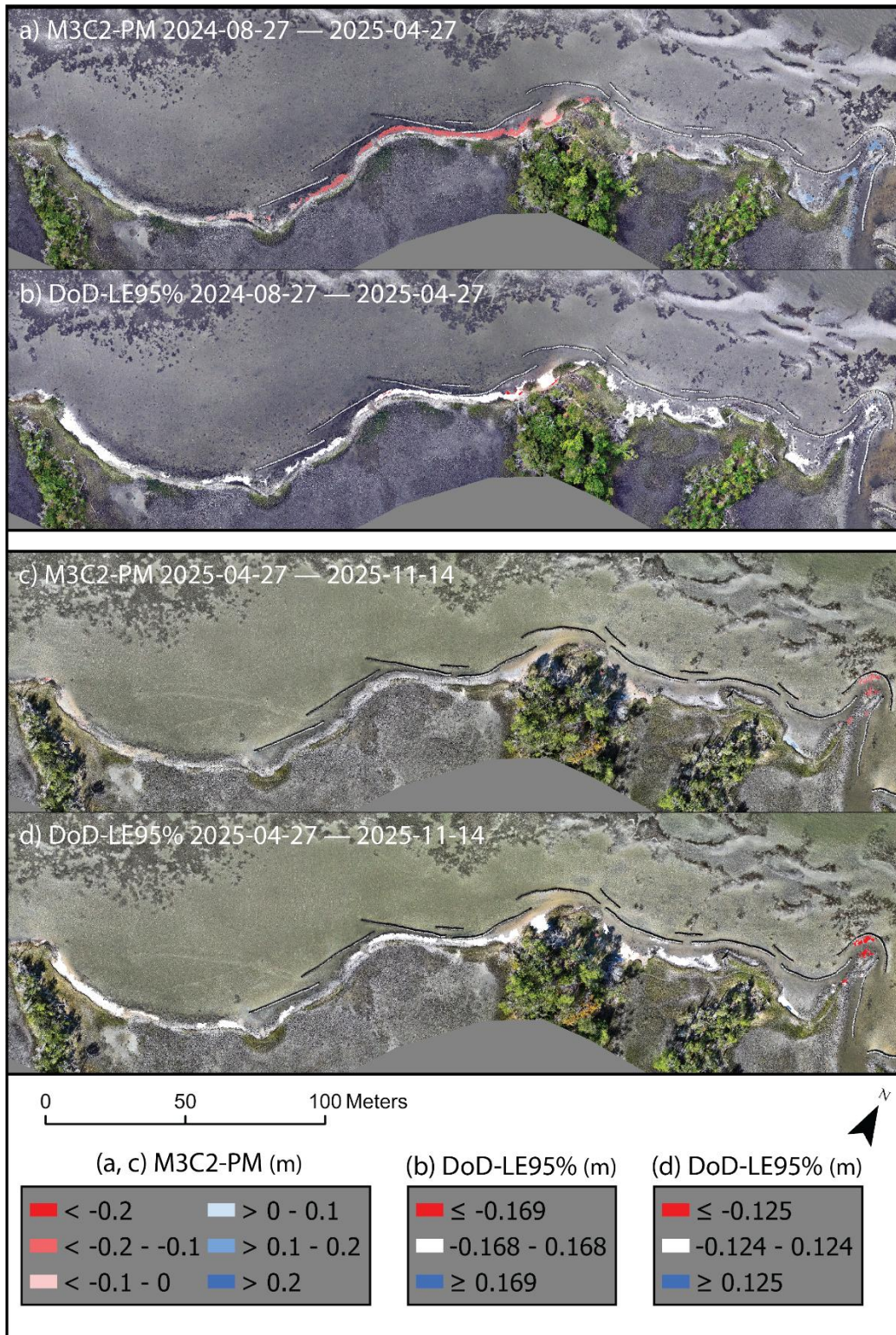


Figure 7. Comparison of elevation differences detected using M3C2-PM and DoD-LE95% approaches for Natrx ExoForms™ topographic surveys. Seasonal M3C2-PM changes are mapped in a and c, and seasonal DoD-LE95% changes are mapped in b and d. Maps a and b are overlaid the April 27th, 2025, orthomosaic and maps c and d are overlaid the November 14th, 2025, orthomosaic. M3C2-PM show distances using the 95% confidence interval and the DoDs show distances using survey specific LE95%.

Table 9. Volumetric change assessment for the seasonal Natrx ExoForms™ topographic surveys.

Fig. 7 Map	Change Detection Method	Survey	Significant Change Area (m ²)	Accretion (m ³)	Erosion (m ³)	Net Volume (m ³)
Map a	M3C2-PM	2024-08-27 – 2025-04-27	256.11	8.56	-18.71	-10.15
Map b	DoD-LE95%	2024-08-27 – 2025-04-27	7.53	0.31	-1.04	-0.73
Map c	M3C2-PM	2025-04-27 – 2025-11-14	40.17	1.37	-3.32	-1.95
Map d	DoD-LE95%	2025-04-27 – 2025-11-14	19.86	0.38	-3.01	-2.62

The annual geomorphic comparison (Fig. 8) was calculated directly between August 27th, 2024 – November 14th, 2025, rather than by summing the two seasonal comparisons. This annual comparison represents an endpoint comparison between August 27th, 2024, and November 14th, 2025, and should not be interpreted as the cumulative sum of the two seasonal comparisons. Over the full year, the site was dominated by erosion (Table 10). This pattern is similar to the August 27th, 2024 – April 27th, 2025, interval, suggesting that the annual endpoint pattern was like the winter-to-spring comparison. Over the full annual endpoint comparison from August 27th, 2024 – November 14th, 2025, the M3C2-PM (Fig. 8 a) again identified more significant change area (106.33 m² versus 23.48 m²), more accretion (2.12 m³ versus 0.97 m³), and more erosion (-10.80 m³ versus -3.08 m³). Across all intervals, accretion volumes were smaller than erosion volumes within the monitored exposed-topography area, indicating net lowering during the first year of observation.

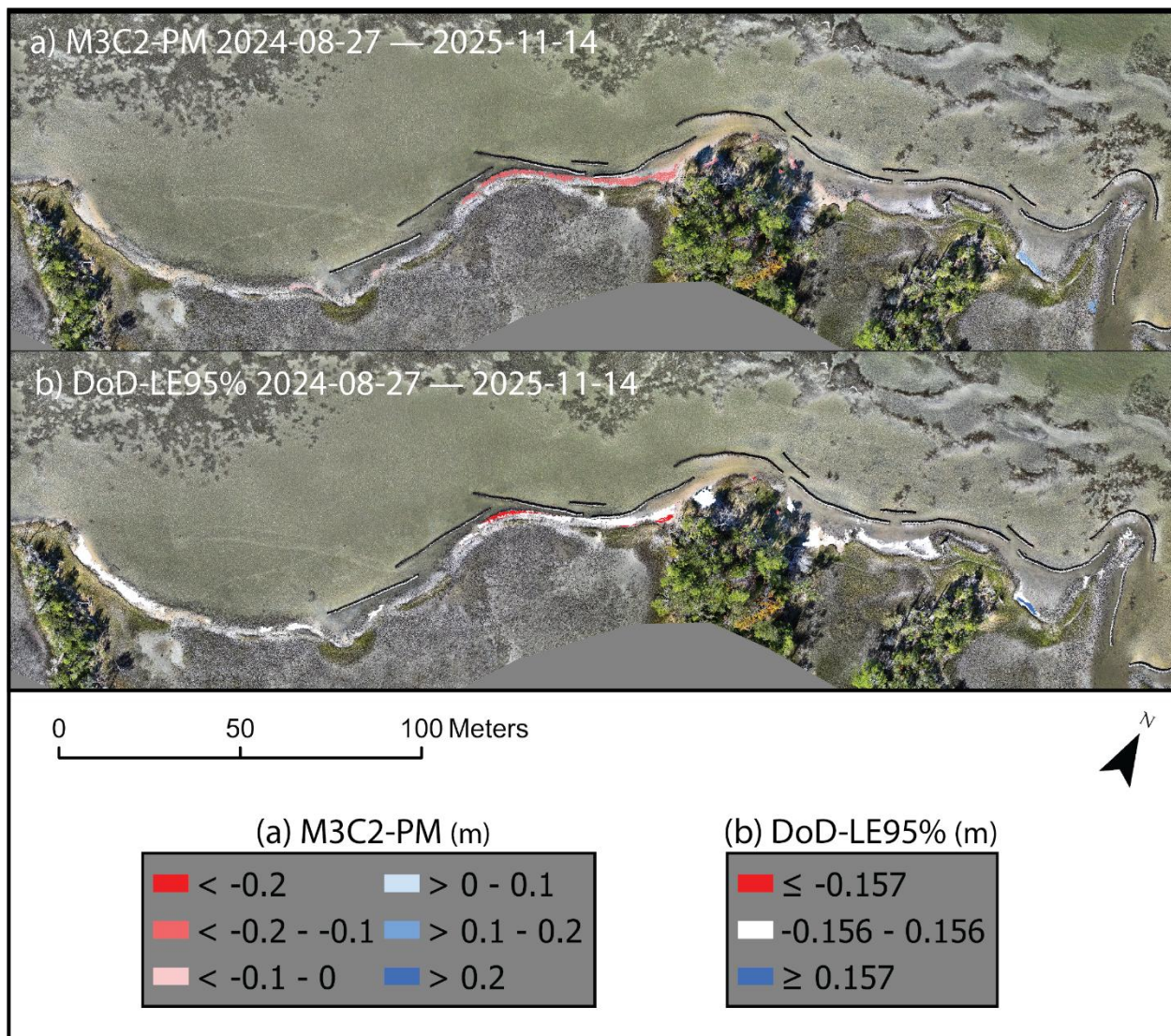


Figure 8. Natrx ExoForms™ M3C2-PM (a) and DoD-LE95% (b) annual topographic changes mapped overlaid the November 14th, 2025, orthomosaic image.

Table 10. Volumetric change assessment for the annual Natrx ExoForms™ topographic surveys.

Fig. 8 Map	Change Detection Method	Survey	Significant Change Area (m ²)	Accretion (m ³)	Erosion (m ³)	Net Volume (m ³)
Map a	M3C2-PM	2024-08-27 – 2025-11-14	106.33	2.12	-10.80	-8.68
Map b	DoD-LE95%	2024-08-27 – 2025-11-14	23.48	0.97	-3.08	-2.12

4.2.3 Natrx ExoForms™ elevation profiles

Elevation profiles were derived to assess transect-scale elevation change for the M3C2-PM and DoD-LE95% results (profile locations and elevation profiles shown in Fig. 9). The top

three panels (b, c, d) show elevation changes based on transects taken from the marsh-edge to the landward-side of the living shoreline, and the bottom three panels (e, f, g) show profiles of the reference site for a total of six elevation profiles. The blue line indicates the baseline pre-installation topography (August 27th, 2024), the orange line is the April 27th, 2025, topography, and the green line is the November 14th, 2025, topography. Natrx ExoForms™ elevation profile 1 (Nx1) shows the site accreting from August 27th, 2024 – April 27th, 2025, along the entire profile, with more sediment gained closer to the living shoreline. From April 27th, 2025 – November 14th, 2025, however, the site erodes below the baseline profile until it gets closer to the living shoreline, where elevations remain closer to the August 27th, 2024, survey baseline. The Nx2 and Nx3 profiles indicate erosion from August 27th, 2024 – April 27th, 2025, and November 14th, 2025; however, Nx2 shows a more consistent lowering across the profile, while Nx3 shows a sharper elevation drop over a shorter profile distance. Across all Nx profiles, there is more variability than what is shown in the reference site. The Reference elevation profile 1 (R1) and R2 transects exhibit more uniform declines, while R3 indicates accretion during August 27th, 2024 – April 27th, 2025, and erosion from April 27th, 2025 – November 14th, 2025, returning closer to baseline elevations by November 14th, 2025. Overall, the Nx profiles show a mix of erosion and accretion and more variability than the reference transects. The reference profiles are shorter due to less intertidal shoreline from the marsh edge to the water level captured during the time of the surveys and show smaller or more uniform changes overall. R1 shows the clearest lowering, R2 shows limited change, and R3 shows accretion from August 27th, 2024 – April 27th, 2025, followed by lowering from April 27th, 2025 – November 14th, 2025.

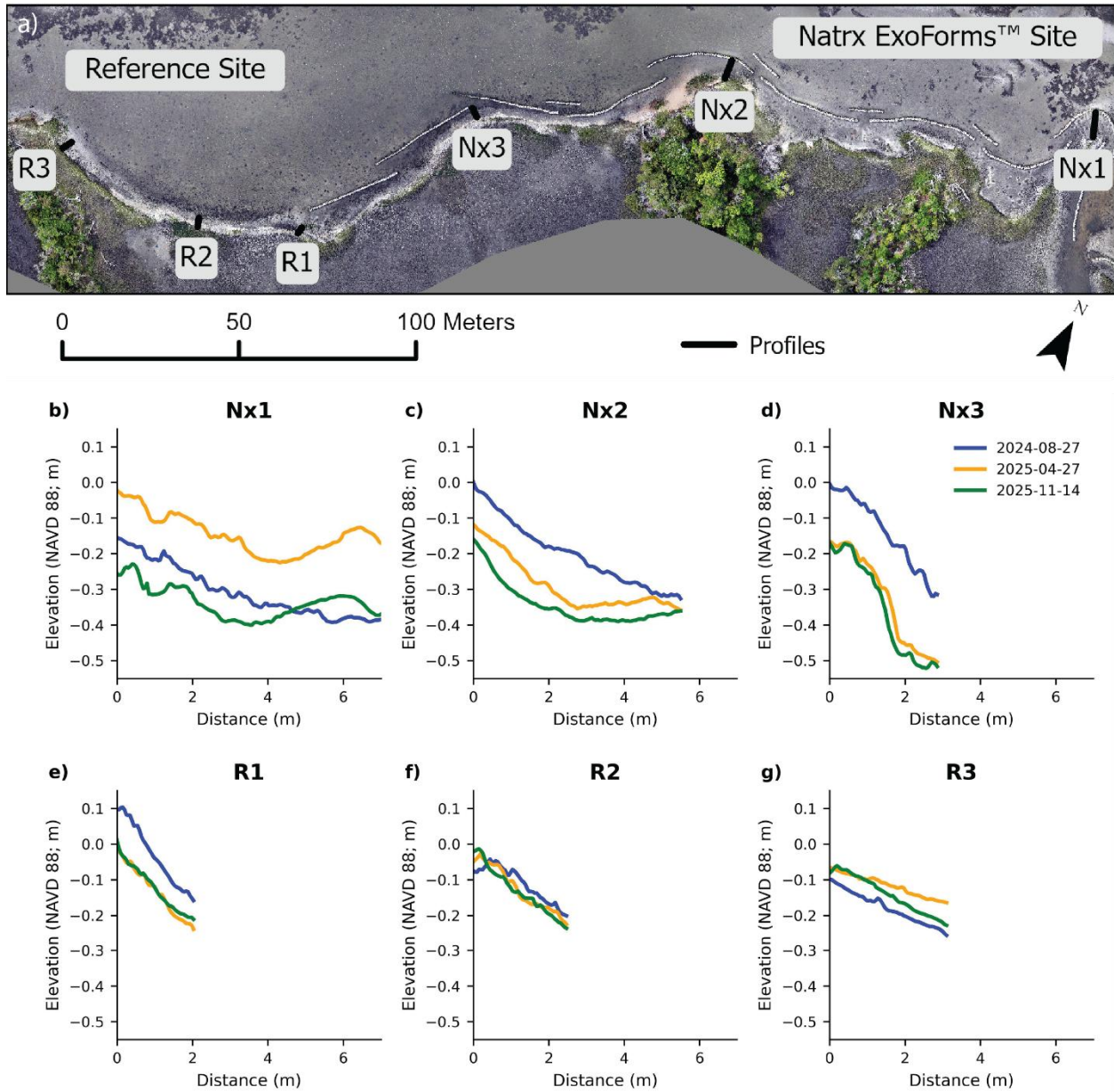


Figure 9. Elevation profile locations for the Natrx ExoForms™ and reference sites overlaid DoD-LE95% for August 27th, 2024 – April 27th, 2025, period. Elevation profiles from the marsh edge to the Natrx ExoForms™ living shoreline (a, b, c). 2D elevations of the reference site are shown in the lower panels (d, e, f)

CHAPTER FIVE: DISCUSSION

5.1 Physical processes geomorphic impact

This seasonal and annual analysis of geomorphic change behind living shoreline structures shows that the strongest elevation and volumetric changes occurred during the first post-installation winter-to-spring interval, when the site was exposed to frequent NNE/NE winds and the breakwater structures were newly installed. Baseline surveys on August 27th, 2024, established pre-installation conditions, and the April 27th, 2025, and November 14th, 2025, surveys captured the first year of post-installation geomorphic response. Together, the seasonal surveys show that high-resolution, uncertainty-aware monitoring was needed to detect subtle sediment redistribution behind the living shoreline structures..

Wind and tide-driven waves are primary drivers of marsh shoreline evolution (Morris et al., 2002, Leonardi et al., 2016), and the timing of the observed geomorphic change aligns closely with these mechanisms. Wind roses constructed from NOAA station 8654863 (BFTN7, Beaufort, BC) illustrate the frequency and distribution of wind speeds and directions recorded during each survey period (Fig. 10). In coastal North Carolina, winds are dominant from the NNE/NE in the winter when they are onshore before switching offshore during the summer from the WSW/SW, shown by the frequency of winds on the rose charts (Fig 10.). The August 27th, 2024 – April 27th, 2024, interval, which showed the greatest geomorphic change, was dominated by frequent NNE/NE winds, with a secondary WSW/SW component (Fig. 10a). These NNE/NE winds likely increased wave exposure and water-level setup along portions of the shoreline, helping explain the broader erosional signal mapped during this interval. Construction of the living shoreline occurred from October 16th – November 14th, 2024, during the transition into the NNE/NE-dominated season, so early post-installation change likely reflects both seasonal

forcing and adjustment to the newly installed structures. The least amount of change was observed during the April 27th, 2025 – November 14th, 2025, survey period, when the highest frequency of winds came from the WSW/SW, although the highest wind speeds were reported for a short duration out of the NE when the shoreline was already protected (Fig. 10b). Across the full Aug. 27, 2024-Nov. 14, 2025, period, winds remained bimodal, with frequent NE/NNE and WSW/SW winds (Fig. 10c). The pre-installation wind rose further shows that NE/NNE winds were already common before construction began (Fig. 10d), providing a useful context for interpreting early site response.

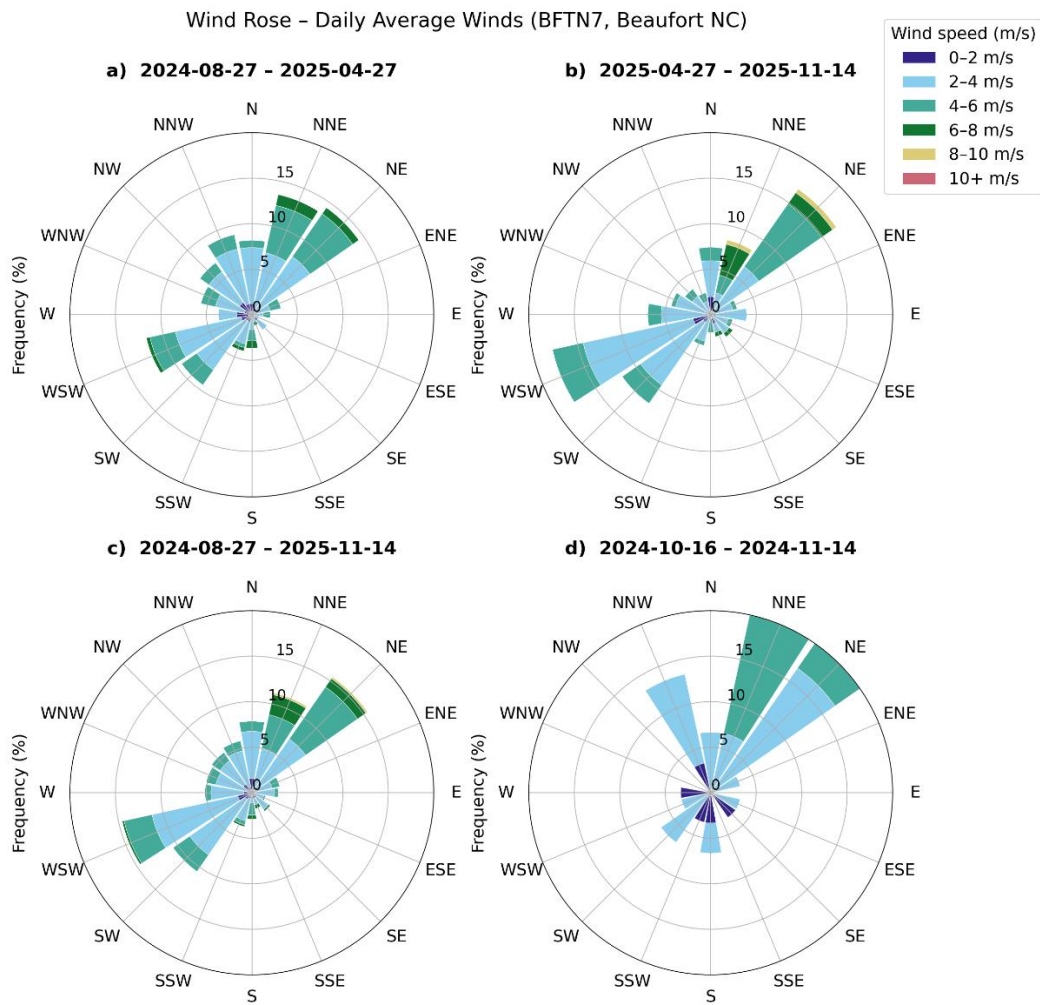


Figure 10. Wind rose charts for the dominant wind direction and speed of NOAA Station BFTN7 for the three survey periods.

5.2 Study limitations

This study employed a SfM-based sUAS framework to quantify fine-scale topographic change, a method widely used in coastal and geomorphic research, but it also has inherent limitations (e.g., Eltner et al., 2016; James et al., 2019; Pettyjohn et al., 2025). SfM reconstructions are highly sensitive to image network geometry, camera calibration, and spatial distribution of tie points, all of which influence the robustness of bundle adjustments and uncertainty of the derived products. Low-relief environments such as salt marshes present challenges including their narrow elevation range and homogeneous surface texture reducing feature detectability which produce high-variance tie points that destabilize the internal photogrammetric geometry (James & Robson et al., 2014; Passalacqua et al., 2015).

These limitations were evident in this study. The sparse point cloud for the August 27th, 2024, Natrx ExoForms™ dataset amplified small geometric inconsistencies and exhibited signs of “bowling” or large-scale bending, an effect well documented in low-relief SfM applications (James et al., 2017). This required the application of a stricter tie point reprojection error (through gradual selection) threshold to reduce uncertainty below sub-decimeter and stabilize the model. Additionally, comparison of camera optimization models demonstrated that Agisoft Metashape’s adaptive camera model fitting reduced systemic error residuals and increased model stability, in this study. Models lacking adaptive camera model fitting (A and C; see Table 3) produced higher RMSE values across all summary statistics indicating a less stable image network geometry when compared to models incorporating adaptive camera model fitting (B and D) which yielded lower errors across all surveys.

Environmental conditions also introduce limitations. Sung glint, water clarity, and depth also contribute to noise in the 3D surface reconstruction—issues commonly reported in shallow-

water SfM studies (Sturdivant et al., 2017; Agrafiotis et al., 2018; Le Mauff et al., 2018; Giulietti et al., 2022). Tidal constraints limited the extent of exposed topography, and onshore winds elevated water levels at low tide. As a result, each survey comparison was further constrained to the overlap of visibly interpretable exposed surfaces, reducing the area available for M3C2-PM and DoD-LE95% analysis.

Collectively, these limitations show why method choice matters in low-relief coastal change detection. M3C2-PM retained more fine-scale, spatially continuous change by comparing the filtered point clouds directly and applying spatially variable uncertainty estimates (Lague et al., 2013; James et al., 2017). DoD-LE95% provided a stricter raster-based estimate of vertical elevation change after DEM generation and thresholding. Using both methods allowed erosion-dominated change to be identified consistently, while also showing that mapped area and volume were sensitive to spatial support, uncertainty treatment, and the exposed-topography mask used for each survey comparison.

5.3 Future work

Geomorphic change along marsh shorelines occur over long periods and are not driven by rapid changes in the environment (Fagherazzi et al., 2012; Kirwan & Megonigal, 2013). Because these processes operate slowly relative to the highly dynamic behavior of sandy shorelines, detecting meaningful geomorphic change in marsh environments requires monitoring strategies that extend beyond a single season or year.

The results of this study reinforce the need for long-term monitoring efforts. While seasonal and annual surveys capture early-stage responses to high-energy events and sediment adjustments to the living shoreline, they also reveal that the majority of detected change occurred during a single high-energy interval (August 27th, 2024 – April 27th, 2025). Subsequent changes

captured were smaller in magnitude reflecting short-term adjustments rather than long-term geomorphic trends. Elevation profiles further showed localized lowering across several transects, while accretion near the living shoreline was limited and spatially variable. These patterns indicate that the system has not yet reached a new equilibrium state and that early responses may not be predictive of long-term trends.

Repeated monitoring efforts spanning multiple years capturing a range of storm seasons, tidal cycles, and vegetation phases is essential to quantify the subtle adjustments that characterize marsh shoreline evolution. Multi-year datasets are particularly important for evaluating living shoreline performance, as ecological and geomorphic benefits often emerge after several years of sediment accretion and structural development (Bilkovic et al., 2016; Smith et al., 2020; Palinkas et al., 2023). Future work should integrate thorough hydrodynamic analysis and ecological indicators like habitat change to develop a deeper understanding of how living shorelines impact marsh shorelines and the entire marsh-intertidal-nearshore system over time.

5.4 Management implications

The geomorphic patterns observed during the first year following installation show that early post-installation conditions were strongly influenced by the timing and magnitude of high-energy events and short-term adjustment processes. The surface lowering detected during the August 27th, 2024 – April 27th, 2025, period reflects change across a survey interval that included pre-installation conditions, construction, and early post-installation adjustment, which should be considered when interpreting volumetric results. Although localized accretion immediately landward of the living shorelines is consistent with sediment trapping during early monitoring, broader shoreline lowering indicates that system-wide stabilization cannot be evaluated from the first year alone. In addition, the reference profile adjacent to the living shoreline substrate

indicated the most erosion compared to the other two unprotected reference profiles. These early responses provide managers with critical insight into how different designs interact with storm-driven processes and can inform decisions about structural spacing, elevation, and the need for adaptive modifications to enhance sediment retention and shoreline protection.

The contrast between the living shoreline performance and reference areas suggest that mapped changes represent meaningful short-term geomorphic responses, while also reinforcing the need for long-term monitoring. The differences in M3C2-PM and DoD-LE95% results further demonstrate that method selection directly influences the volumetric changes detection and thus management interpretation. Incorporating uncertainty-aware point cloud-based approaches into geomorphic change monitoring approaches can improve interpretation of living shoreline performance assessments and reduce the risk of overinterpreting early-stage outcomes. Ultimately, long-term, integrated geomorphic and ecological monitoring is essential for understanding how living shorelines develop, accumulate sediment, and support marsh recovery enabling managers to make informed decisions about design optimization and adaptive management.

CHAPTER SIX: CONCLUSION

This study assessed early-stage seasonal and annual geomorphic change patterns of a marsh-backed shoreline where Natrx ExoForms™, a living shoreline substrate, were installed. It demonstrates that high-resolution sUAS-SfM monitoring, paired with uncertainty aware change detection methods, provide a framework for quantifying early geomorphic responses to living shoreline installation across low-relief marsh shoreline environments. Seasonal and annual analyses reveal that high-energy wind and wave driven processes exert a strong influence on short-term shoreline behavior, with most of the observed sediment redistribution occurring during the August 27th, 2024 – April 27th, 2025, interval. Subsequent geomorphic adjustments reflected continued physical forcing and early post-installation sediment redistribution, including localized accretion landward of the installations. The comparison of M3C2-PM and DoD-LE95% further highlights the value of including a point-cloud-based approach when quantifying geomorphic change because it can retain subtle, spatially distributed fine-scale change that may be reduced during raster-based differencing. Collectively, these findings underscore that early-stage geomorphic responses should not be interpreted as indicators of long-term performance and that multi-year, uncertainty-aware monitoring is essential for evaluating how living shorelines influence sediment dynamics, marsh stability, and nearshore habitat structure over time.

CHAPTER SEVEN: REFERENCES

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