

# Quantifying Surface Processes Using Remote Sensing: Accretion in River Deltas and Migration of Barchan Dunes

Thesis by  
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The Caltech logo, featuring the word "Caltech" in a bold, orange, sans-serif font.

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## ABSTRACT

Detecting and quantifying geomorphic change in sedimentary landscapes is essential for understanding how surface processes respond to environmental forcing and for addressing societal challenges. This thesis investigates how sediment is distributed in river deltas and aeolian dune fields using remote sensing. In river deltas, sediment accretion maintains land elevation relative to sea level, whereas in arid regions, sand mobility controls dune migration, which may overwhelm civil infrastructure. Despite advances in constraining boundary conditions such as sediment supply, sea-level rise, and wind regimes, the internal dynamics that regulate sediment retention and transport remain poorly understood. In Chapter 2, I quantify decadal accretion patterns in the Wax Lake Delta (WLD), Louisiana, using repeat lidar surveys. I show that accretion exhibits strong spatial variability, with higher rates at island edges and within elevations associated with moderate inundation frequency in the high-intertidal zone. Downstream topographic gradients suggest that the delta tends to maintain an equilibrium gradient that is coupled to floodwater surface gradients, while vegetation and island morphology cause local variations. I further demonstrate that large flooding events contribute disproportionately to elevation gain and enhance sediment trapping. In Chapter 3, I show that secondary channels can deliver sediment to sediment-starved island interiors, increasing their accretion rates to levels comparable to those at levees and helping deltaic islands extend accretion beyond their edges. These channels cycle through phases of initiation, progradation, and backfilling, consistent with previous numerical predictions. Because deposition along secondary channel lobes is concentrated in topographic lows, their autogenic cycles may redistribute sediment across island interiors through time, promoting more spatially uniform island accretion through compensational stacking of channel lobes. In Chapter 4, I explore the response of barchan dune fields to changes in environmental conditions. I develop an automated workflow to detect, segment, and track barchan dunes from satellite imagery and apply it to a dune field in Qatar. I show that coastal dunes migrate at rates comparable to those of inland dunes, indicating that reduced interdune spacing near the coast is not due to modern stabilization. Instead, the present morphology likely reflects an inherited dune-field organization that was reworked following an ancient marine transgression. Using migration rates to back-propagate dune positions, I show in Chapter 5 that dune arrival times along the northern coast coincide with the mid-Holocene filling of the Arabo-Persian Gulf, which likely terminated sediment supply. Back-projected dune positions further suggest that sediments were sourced from paleo-river systems linked to the Zagros Orogeny rather than from Arabia. Together, these results demonstrate how remote sensing of geomorphic change can be used to quantify sediment trapping, identify dominant surface processes, and reconstruct ancient environmental conditions.

## PUBLISHED CONTENT

### ***Journal Publications:***

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- Hussain Alqattan participated in the project conception, compiled, processed, and analyzed data, and co-led the writing of the manuscript.
- The material of this published paper has been used for Chapter 2.

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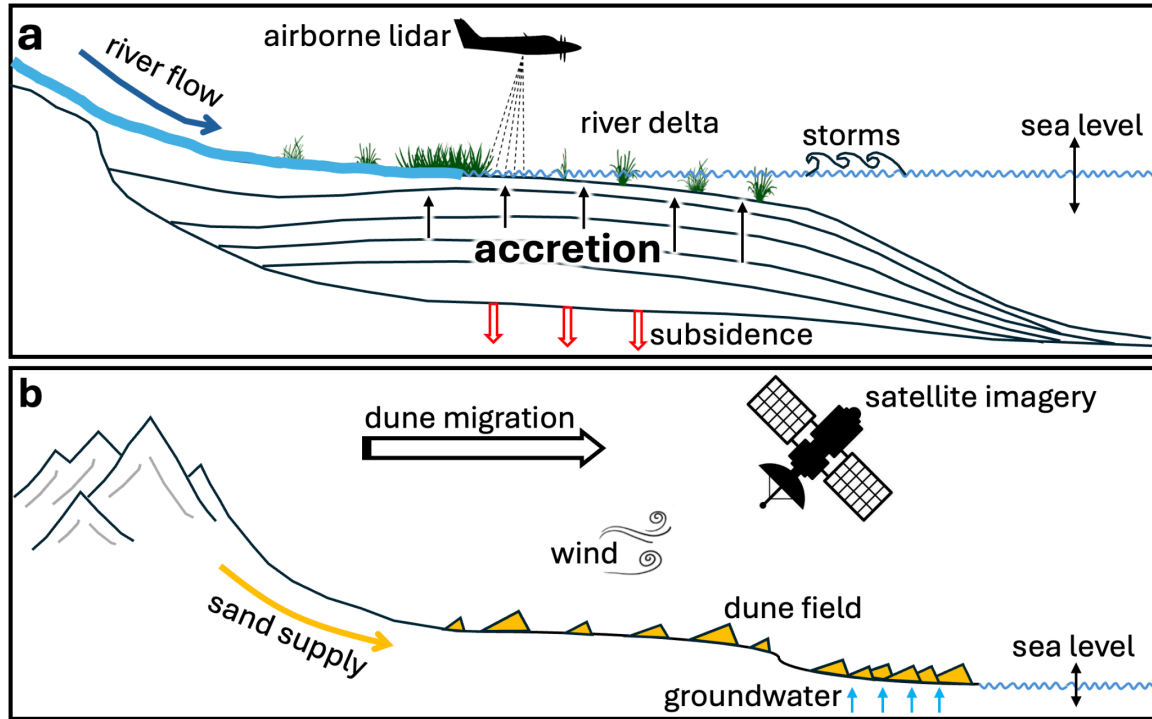
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## CHAPTER 1: INTRODUCTION

In this thesis, I investigate sediment transport and landscape change in river deltas and aeolian dune fields using remote sensing observations. I focus on these environments because both evolve through the transport and storage of sediment across large spatial scales, yet their responses to changing environmental forcings remain difficult to quantify using conventional field methods. Detecting and quantifying geomorphic changes in sedimentary landscapes, such as deltas and aeolian dunes, is important for addressing societal and environmental challenges. The vertical buildup of sediments (i.e., accretion) in deltas maintains an elevation surplus that protects deltaic lands from submersion as sea levels rise (Figure 1a; Twilley et al., 2019). In addition, sediment retention in deltaic lands promotes the burial of organic carbon, thereby serving as an important long-term sink for atmospheric CO<sub>2</sub> (Leithold et al., 2016). Growing in Saudi Arabia also motivated my interest in aeolian systems, where sand mobility can obstruct roads, overwhelm infrastructure, and complicate human development in arid regions (Bouarfa et al., 2025). Sand mobility can intensify in the future as climate change and land-use changes are projected to increase wind strength and reduce vegetation cover in many regions (Baas & Delobel, 2022; Syvitski et al., 2022). Predicting whether deltas drown or dunes migrate ultimately requires understanding how sediment is distributed and stored across landscapes.

Patterns of sediment transport and retention are controlled by both external boundary conditions (Figure 1; e.g., sediment supply, sea level, wind regime, and subsidence) and by internal dynamics (Romans et al., 2016). For instance, deltaic maintenance depends on the rates of sediment supply and retention relative to rates of sea-level rise and subsidence (Figure 1a; Twilley et al., 2019). Catchment sediment production of many major river systems (Wittmann et al., 2020), their sediment-routing pathways (Martin & Lamb, 2025), and the magnitudes of their sediment fluxes channeled to the coast are well constrained (Giosan et al., 2014). However, how deltas internally distribute and trap sediment under changing sea levels remains poorly understood (Fagherazzi et al., 2012). Internal dynamics in deltas may include reduced sediment settling velocity due to flocculation (Lamb et al., 2020) or due to vegetation emergence (Mudd et al., 2010).

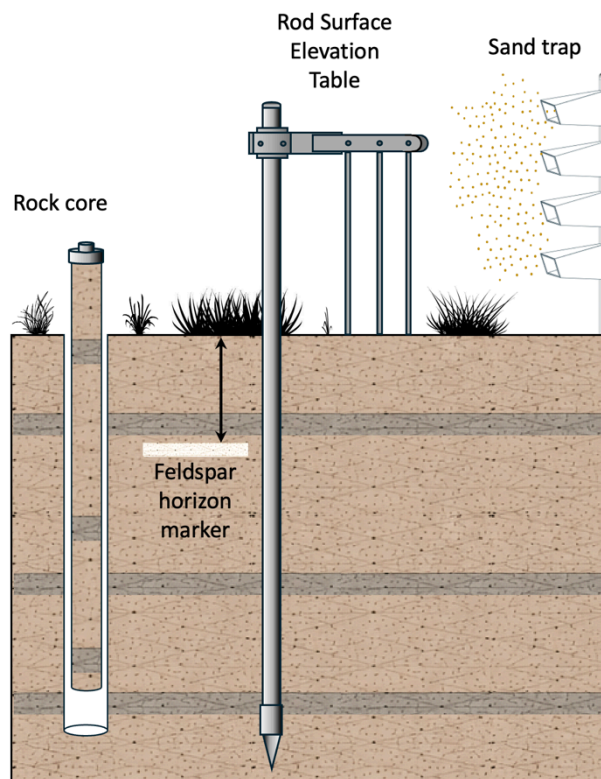


**Figure 1.** Schematic of sediment routing systems, inspired and modified from the conceptual framework of Romans et al. (2016). Both systems, (a) a river delta and (b) a coastal dune field, are components of larger sediment-routing systems that transfer sediment from mountain source regions to depositional sinks. Along these pathways, sediment transport and storage vary spatially due to changing local conditions and internal dynamics.

Aeolian dune migration is another important geomorphic process that remains poorly constrained. Using sediment transport laws, dune migration rates can be predicted from known wind regimes and dune sizes (e.g., Daudon et al., 2024). However, as with other surface processes, internal dynamics and variability in local conditions may cause dune migration rates to deviate from predictions. Vegetation cover, topography, and moisture from precipitation or groundwater may increase bed roughness or grain cohesion, thereby reducing sand mobility (Figure 1b; Davidson-Arnott et al., 2008; Xu et al., 2015). Evidence suggests that the position of dunes within the dune field may alter their migration rate due to variable sand availability and the influence of neighboring dunes on downwind transport capacity (Al-Masrahy & Mountney, 2013). Dune-dune interactions may also regulate interdune spacing and dune-size distributions in dune fields and influence the overall migration rates of these fields (Genois et al., 2013).

## Remote sensing for measuring geomorphic change

A central goal of this thesis is to use remote sensing observations to quantify geomorphic change across entire sedimentary landscapes. Analyzing the impact of varying boundary conditions on surface processes requires estimating how geomorphic changes vary in time and space (how rapidly sediment accumulates vertically and migrates laterally). Direct observations using conventional methods (e.g., point measurements; Figure 2) are spatially limited in their ability to capture variability at the scale of a delta or dune field (Allen, 2008). Numerical models are also beneficial, but their predictive capability depends on the physical processes they incorporate under ideal conditions, many of which are poorly constrained.



**Figure 2.** Point-based methods (rock cores, feldspar marker horizons, rod surface-elevation table, and sand traps) used in the field to quantify sediment transport and accumulation in geological environments.

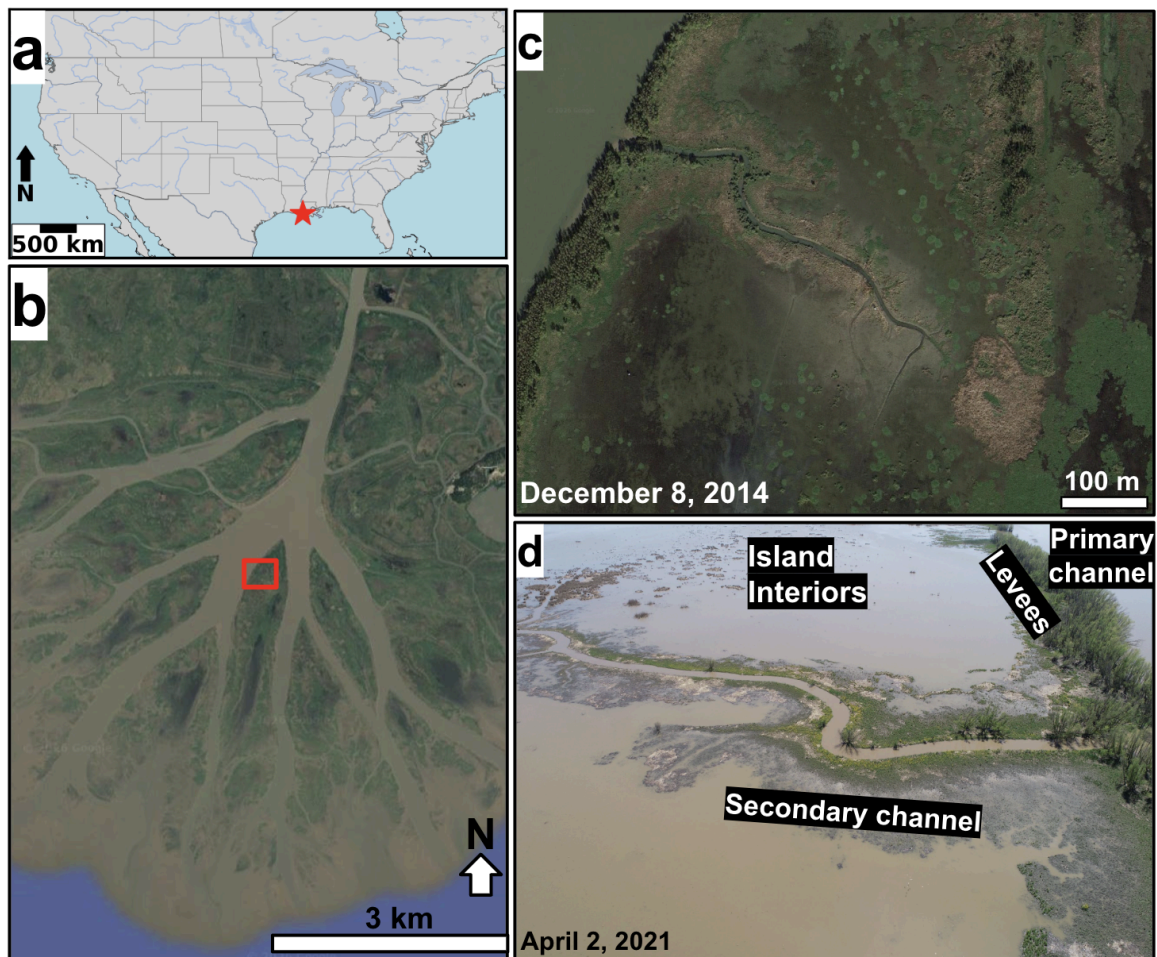
Remote sensing technologies (e.g., lidar and satellite imagery) enable monitoring landforms at large spatial scales. Repeated surveys enable measurement of change rates (e.g., Okyay et al., 2019; Jiang et al., 2025). In addition to mitigating geohazards, when theory can link measured features (e.g., topographic gradients) or change rates (e.g., deltaic accretion and dune migration) to formative boundary conditions (e.g., river

discharge, wind strength), remote sensing can be a useful tool for interpreting ancient paleoenvironmental conditions (e.g., Ganti et al., 2014; Chanteloube et al., 2022; Gunn, 2023).

### **Research questions**

River deltas worldwide are home to approximately ~300 million people (Edmonds et al., 2023), but they are losing land rapidly due to reduced sediment supply (Blum & Roberts, 2009). It is thus important to understand whether surviving deltas retain river sediments, at what rate they build land relative to rising sea levels, and what mechanisms enable them to build land. These broader questions motivate the component of this thesis dealing with deltas, which uses repeat lidar to examine sediment retention, accretion patterns, and land-building processes in the Wax Lake Delta (WLD), south Louisiana, USA.

In Chapter 2, I use repeat lidar surveys from 2009, 2011, 2012, and 2013, together with a recently published 2020 survey (Nghiem et al., 2022), to map decadal rates of accretion in WLD (Figure 3a-b). Wax Lake Delta has been uniquely gaining land, at least through 2016, despite an overall trend of land loss across the rest of the Mississippi Deltaic Complex (Couvillion et al., 2017). First, to evaluate the delta resilience, I estimate the fraction of river-sediment load trapped in the delta and compare delta-scale average decadal accretion rates with rates of relative sea-level rise. Next, I analyze the spatial patterns of accretion across the delta. In doing so, I investigate whether different regions of the delta build land at different rates and which deltaic mechanisms most likely control these spatial differences. Thus, Chapter 2 asks: At what rates does WLD retain river sediment and build land relative to relative sea-level rise, and how do accretion rates vary spatially across the delta?



**Figure 3.** (a) Location map of Wax Lake Delta in south Louisiana along the Gulf of Mexico coast. The red star shows the delta location. (b) Google Earth satellite image of Wax Lake Delta showing deltaic islands separated by primary channels. (c) Google Earth satellite image of a secondary channel, with its location marked by the red box in panel (b). (d) Drone image of the secondary channel connecting the primary channel to island interiors.

After investigating accretion variability in the delta, I analyze whether WLD is converging toward a topographic steady state. A topographic steady state would reflect a balance between accretion that builds land and elevation loss (e.g., due to subsidence). There are multiple possible forms for this balance, however. The delta may converge toward a quasi-equilibrium uniform elevation as it keeps pace with mean sea levels (Morris et al., 2002), or multiple stable elevation platforms mediated by vegetation zonation (Marani et al., 2010). Both conceptual models have been proposed for WLD previously (Wagner et al., 2017; Smith et al., 2020). Identifying whether the delta would converge to these equilibrium elevations, or to another model, and which

conceptual model best describes WLD, helps us determine which dominant environmental forcing(s) shapes the steady-state topography of river deltas (e.g., vegetation, sea level, etc.). Thus, Chapter 2 also asks: Does WLD evolve toward a topographic steady state, and if so, what conceptual model best explains its equilibrium topography?

Typically, accretion rapidly decreases with increasing distance from primary channels (Figure 3b), leaving interior lands sediment-starved (Day et al., 2008). One mechanism proposed to replenish these deltaic lands is sediment delivery through secondary channels (Figure 3c-d; Salter & Lamb, 2022), yet their contribution to deposition rates relative to those at island edges remains poorly constrained. In Chapter 3, I use a segment of the repeat lidar dataset (2009, 2012, 2020) to explore these secondary channels. Using repeat lidar differencing, I quantify deposition rates across these channels with extensive spatial coverage and investigate whether these rates are sufficient to replenish land interiors. I also investigate whether these channels are unstable features that cycle through incision and progradation, as previously hypothesized by numerical models (Nienhuis et al., 2018; Salter & Lamb, 2022). Thus, Chapter 3 asks: Do secondary channels transport sufficient sediment into delta interiors to offset sediment depletion away from channels, and are these channels stable or auto-cyclical?

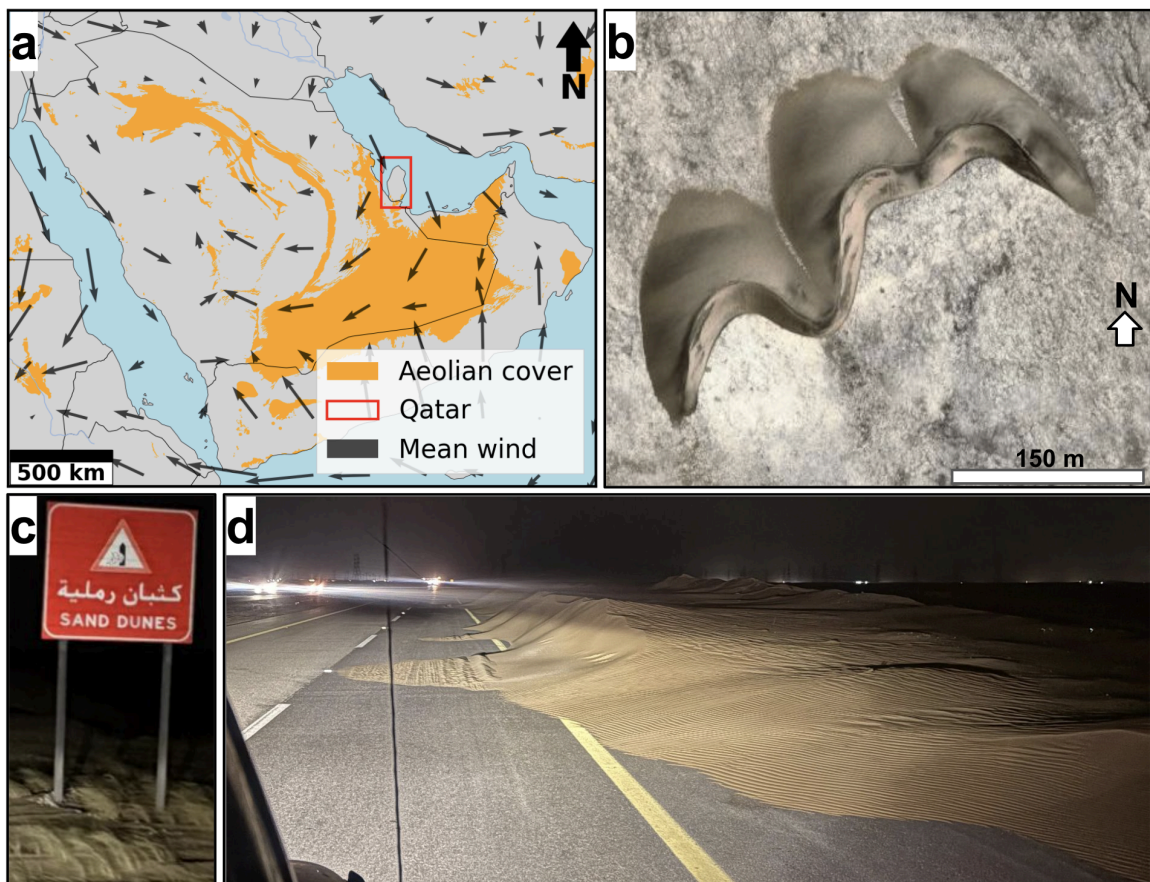
Aeolian dune fields present a parallel sediment-transport challenge. Barchan dunes (Figure 4b) are ideal bedforms for measuring sand encroachment on infrastructure (Figure 4 c-d), and for inferring the variable effects of local conditions on aeolian sand transport. This is because they are formed by approximately unidirectional winds, are commonly isolated, respond rapidly to changes in flow conditions, and exhibit a crescentic shape that reveals their migration direction (Figure 4b). These characteristics motivate the aeolian component of this thesis, which uses satellite imagery to measure barchan dune migration in Qatar and to test how migration rates vary across a dune field.

Satellite images have been used in several arid regions worldwide to relate barchan dune migration rates to local conditions (Jiang et al., 2025). To measure these rates, image-correlation methods, such as COSI-Corr, have been used, but they have limitations (Vermeesch & Leprince, 2012). Such techniques rely on image textures that are preserved between image acquisitions and that do not move too rapidly. Correlation search windows can also introduce bias by combining signals from moving dunes and immobile bedrock. Alternatively, barchan migration can be measured by isolating individual dunes before tracking them. To avoid labor-intensive manual measurements, barchan dunes have been detected and segmented using deep learning models over entire dune fields or even entire planets (Rubanenko et al., 2021). However, using these workflows to track barchan dunes through time remains rare (Wang et al., 2026). This



limitation motivates Chapter 4, where I develop an automated workflow that combines dune detection, segmentation, and tracking to measure barchan dune migration rates from satellite imagery.

In Chapter 4, I apply this automated workflow to the barchan dunes in Qatar (Figure 4a) and validate the results using a manually measured dataset (Michel et al., 2018). This dune field contains mostly isolated dunes upwind, but more complex and tightly packed dunes downwind near the southern coast. This spatial transition provides an opportunity to test whether dune migration changes systematically across the dune field. The smaller interdune spacing near the coast may reflect a slowdown in migration due to changes in local conditions such as moisture content, topography, sediment availability, or dune-dune interactions. Thus, Chapter 4 asks: Can automated remote sensing workflows reliably detect, segment, and track barchan dunes across an entire dune field, and do migration rates differ significantly between inland and coastal barchan dunes in Qatar?



**Figure 4.** (a) Map of Arabia showing aeolian sand cover and the location of Qatar. (b) Google Earth satellite image showing an example of barchan dunes in Qatar. (c) Road



sign in Saudi Arabia warning of sand dune encroachment onto highways. (d) Sand dunes advancing onto a highway in Saudi Arabia, posing a hazard to vehicles.

The barchan dunes in Qatar also provide an opportunity to use modern dune migration to reconstruct past sediment-routing pathways. These dunes appear to be cut off from their sand source because no new dunes have formed for more than 60km upwind toward the northern coast. The termination of sediment supply has been hypothesized to coincide with the Arabo-Persian Gulf reaching its present-day levels (Kassler, 1973). Previous studies used back-propagation of barchan dunes based on modern migration rates to constrain this geological event. However, these studies either relied on small datasets and yielded imprecise time frames (e.g., 16 dunes; Engel et al., 2018), or used the average migration rates of all barchan dunes (Embabi & Ashour, 1993). In addition, both studies traced the source of the dunes to Arabia (Embabi & Ashour, 1993; Engel et al., 2018). These approaches may obscure spatial variability in dune migration, especially if inland and coastal dunes migrate at different rates.

In addition, previous studies traced the source of the dunes to Arabia (Embabi & Ashour, 1993; Engel et al., 2018), whereas heavy mineral assemblages indicate that aeolian dunes in Qatar may derive from the Zagros orogeny in Iran across the Arabo-Persian Gulf (Garzanti et al., 2013). While heavy-mineral assemblages can identify the sediment source region, they do not reveal the pathway or timing of sediment transport (Allen, 2008). Therefore, Chapter uses dune migration not only as a measure of modern dune mobility, but also as a tool for reconstructing sediment-routing history. Using the workflow developed in Chapter 4, I measure migration rates for all detectable barchan pairs and propagate dune positions backward toward the northern coast to estimate their arrival times. I then compare these arrival times with independent geochronological constraints indicating Gulf filling at ~5-7 ka during the mid-Holocene and evaluate, based on their back-propagated positions, whether the dunes were sourced from Zagros- or Arabia-derived deposits. I also test scenarios in which the overall migration of the dunes differs from present-day rates. Thus, Chapter 5 asks: Can present-day barchan dune migration rates be used to reconstruct the timing and pathways of sediment transport associated with Holocene filling of the Arabo-Persian Gulf, and do these reconstructions support Zagros- or Arabia-derived sediment sources?

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## CHAPTER 2: REPEAT LIDAR REVEALS PATTERNS OF ISLAND ACCRETION IN A RAPIDLY GROWING RIVER DELTA

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### Abstract

River deltas are losing land where accretion fails to keep pace with subsidence and sea-level rise. However, it remains challenging to quantify accretion rate on deltas and understand its spatial and temporal variability. Here, we leveraged five repeat airborne laser mapping (lidar) to quantify accretion rates across Wax Lake Delta (WLD), Louisiana, USA, a growing branch of the Mississippi-Atchafalaya system. We removed water and low-lying vegetation returns, applied vertical co-registration, and used a local accretion monitoring station to parse lidar elevation change into shallow subsidence and sediment accretion. Accretion and elevation-change rates between 2009-2020 averaged  $4.1 \pm 3.7$  cm/yr and  $1.2 \pm 1.3$  cm/yr, respectively, which exceeded the rate of relative sea-level rise ( $1.2 \pm 0.83$  cm/yr) and corresponded with a sediment trapping efficiency of ~22%. Accretion was concentrated near island edges where the land surface was within the intertidal zone, with lower accretion rates toward island interiors. While flattening of the downstream delta gradient was apparent between 2009 and 2013, possibly due to the 2011 major flood, the gradient increased back to  $1.1 \times 10^{-4}$  m/m in 2020, similar to the 2009 value, suggesting a recovery towards an equilibrium gradient set by the flood surface water profile. Our findings imply that delta-scale accretion patterns are set by feedbacks between elevation and flood-water inundation frequency that controls local sediment supply, whereas vegetation and island morphology cause local variations in accretion by modulating sediment trapping.

### 1 Introduction

River deltas are important coastal lands, providing home for nearly half a billion people (Edmonds et al., 2020; Ericson et al., 2006) and serving as a major global carbon sink (Allison et al., 2007; Shields et al., 2017). Alarming, most deltas are facing submersion

(Syvitski et al., 2009). The Mississippi Deltaic complex, for example, is estimated to have already lost 50 km<sup>2</sup> of land annually between 1984 and 2020 (Jensen et al., 2022). This land loss is caused by some combination of reduced riverine sediment input behind dams and manmade levees, compaction of fine-grained deposits, extraction of groundwater, oil, and gas from the subsurface, and eustatic sea-level rise (Edmonds et al., 2020; Ericson et al., 2006; Nienhuis et al., 2017; Syvitski, 2008; Zoccarato et al., 2018). By the end of the century, 5% of all global deltaic lands are expected to be lost (Nienhuis & Wal, 2021). To combat submersion, deltas must deposit sediment faster than the combined rates of sea level rise and total subsidence (relative sea level rise). However, it remains unclear which parts of a river delta will lose land because sediment accretion is variable in space and time, difficult to measure, and therefore poorly constrained.

River deltas are composed of a bifurcating network of distributary channels that bound deltaic islands. Accretion is governed by processes that supply sediment to the delta top and trap sediment on it (Blum and Roberts, 2009). Sediment supply is controlled by river discharge that brings sediment from upstream and marine processes that supply sediment from downstream, both of which are variable in space and time. For example, during floods, sediment is routed through the bifurcating channel network, and it spills onto islands where flood waters overtop levees or through secondary channels (Passalacqua, 2017). Thus, the supply of fluvial sediment is greatest near the delta apex and the main river channels (Syvitski & Saito, 2007). Likewise, large storms can mobilize sediment offshore and through waves, tides, and storm-driven currents, this material can be transported landward onto the delta (Roberts et al., 2015). Thus, storms might preferentially supply sediment to the most seaward parts of the delta, or to island interiors where elevations are low (Tweel & Turner, 2012). In addition, sediment supply is affected by delta elevation; the downstream parts of deltaic islands tend to have low-elevation levees, promoting greater water and sediment exchange with primary channels, compared to upstream islands (Twilley et al., 2019). These observations point to storms, floods, and tides as important temporal controls on sediment supply, and the distance from the delta apex, distance from the primary channels, and ground elevation as important spatial controls on sediment supply.

Sediment accretion is not only governed by supply, but also sediment must settle through the water column and deposit on the seabed. Given that most of the sediment load in lowland rivers is mud with low settling velocities, it is not surprising that estimates for sediment trapping efficiencies on subaerial deltaic lands are relatively small (range from 10 to 20%; Turner et al., 2006; Giosan et al., 2013; Wu et al., 2023). Thus, trapping efficiency could be the rate-limiting process determining accretion rather than supply. Like sediment supply, the sediment trapping efficiency also varies in space and time. For example, vegetation is thought to strongly increase sediment trapping

efficiency by both binding sediment (Mudd et al., 2010) and by slowing the flow, which enhances friction, encouraging settling, and preventing reentrainment from the bed (Mudd et al., 2010; Wright et al., 2018). However, despite enhanced sediment trapping, dense vegetation can also divert flow to less resistant pathways, thereby reducing local sediment supply (Temmerman et al., 2005; Nardin and Edmonds, 2014; Nardin et al., 2016). In addition, vegetation itself can lead to accretion directly through the accumulation of below-ground organic material (Twilley et al., 2019). Given that vegetation type and density vary across the delta, and can change seasonally, we might expect trapping efficiency also to vary in space and time (Beltrán-Burgos et al., 2023). Moreover, slower flow speeds, greater settling rates corresponding to enhanced flocculation or coarser particles, and shallower water depths should all favor a greater trapping efficiency (Pethick, 1993; Marani et al., 2010; Nghiem et al., 2022). Given the non-uniform flow, variable water depths, and sediment-size segregation across deltas (Syvitski & Saito, 2007), all of these processes could lead to variable accretion rates. Do accretion rates vary spatially across a delta and depend on local elevation ecogeomorphic zones?

Given the spatial and temporal variability in both sediment supply and trapping efficiency on deltas, it is not immediately clear if and how deltaic islands maintain a topographic steady state (Moffet et al., 2015; Salter and Lamb, 2022). By topographic steady state, here we mean a dynamic steady state in which the local sediment bed elevation relative to sea level is quasi-stable and set by a balance between accretion, total subsidence (local and regional subsidence), and sea level rise (i.e., relative sea level rise). For example, consider the simplified case where relative sea level rise varies little across a delta. To reach a topographic steady state, feedbacks must exist to drive accretion rates towards a constant value to match relative sea level rise despite the great variability in the processes that determine the local sediment supply and trapping efficiency (Morris et al., 2002). The primary mechanisms that control such feedback on river deltas are unclear.

One possible feedback mechanism that is common in wetlands is through land elevation: where elevations are low, they are flooded and receive sediment more often, resulting in accretion, colonization by plants as water depths shallow, and enhanced sediment trapping that builds land even higher (Fagherazzi et al., 2012; Mitsch et al., 2023). However, when elevations approach sea level, inundation occurs less frequently, slowing accretion (Morris et al., 2002; Day et al., 2007). This mechanism should result in deltaic land that tends towards an optimum elevation, which we call the constant elevation hypothesis. The constant elevation hypothesis has been proposed for coastal wetlands (Morris et al., 2002) and for some river-dominated deltas (Wagner et al., 2017). Alternatively, the zonation of vegetation species along the elevation profile, combined with its influence on accretion, could produce multiple distinct equilibrium



elevations. This vegetation-mediated equilibrium has been observed and extensively studied in salt marshes (Marani et al., 2010; Marani et al., 2013) and also has been proposed for some river deltas (e.g., Smith et al., 2020).

Another possible feedback mechanism that is common for floodplain-bound rivers is for the floodplain elevations to track river water surface elevations during floods, which decline downstream, often forming a concave-up profile (e.g., Smith, Mason, et al., 2020). In this mechanism, rivers maintain a certain downstream water surface gradient to pass the water and sediment discharge during floods. Levees grow to a similar elevation as the local water surface elevation because overbank flooding causes accretion up to but not exceeding the water surface, similar to the stabilizing feedback in the constant elevation hypothesis (e.g., Pizzuto, 1987; Mason and Mohrig, 2019). However, in this case, since water surface elevations decline downstream, the land would tend toward an equilibrium elevation profile rather than a constant elevation. The downstream gradient, in addition, could be influenced by the balance between river sediment supply and trapping (Syvitski & Saito, 2007).

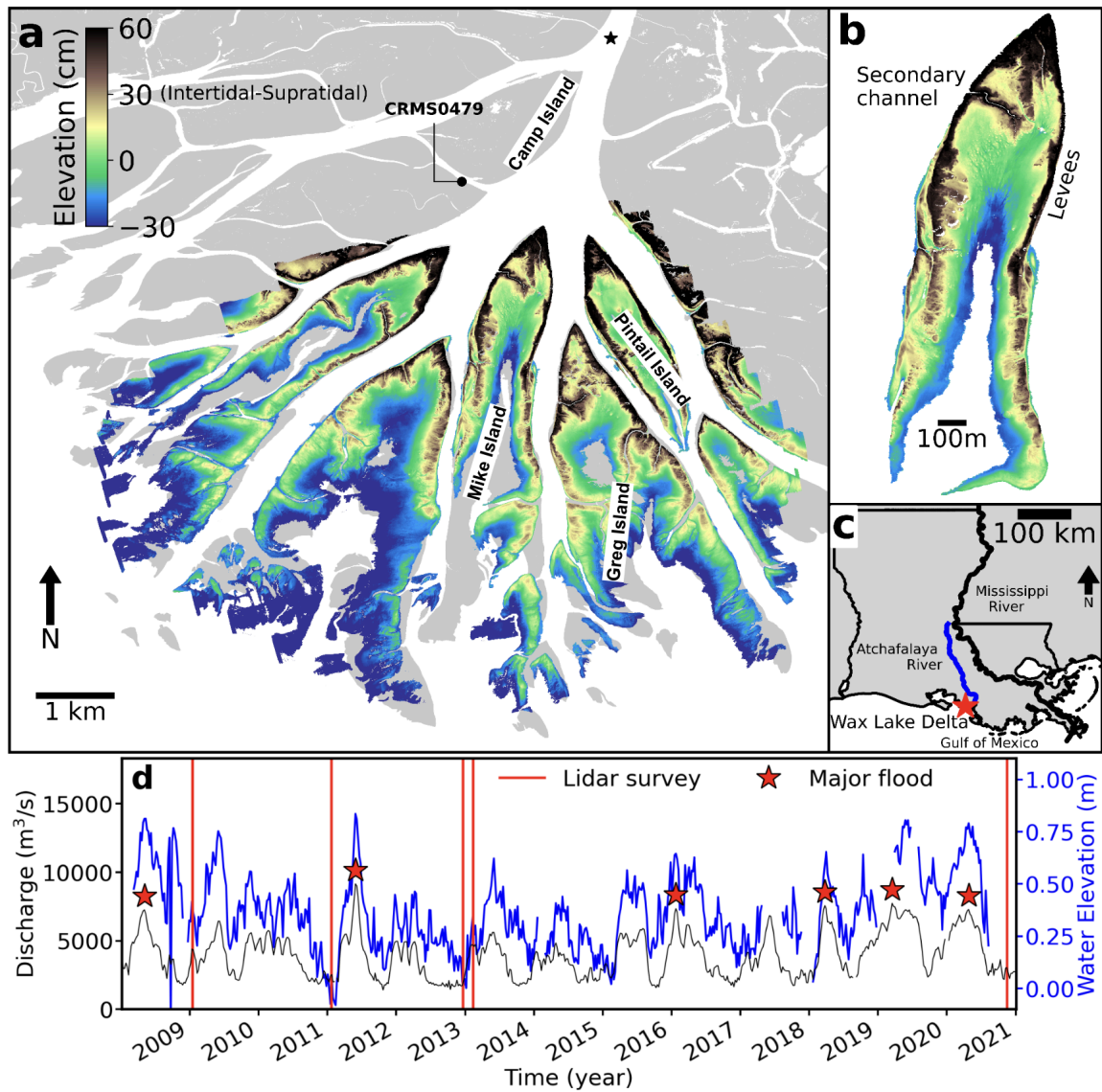
Whether these equilibrium states exist, how they emerge across space, and the averaging time required to achieve equilibrium given storms, floods, and other events remains poorly constrained. Addressing these unknowns requires resolving accretion rates in space and time. These measurements, however, are difficult to obtain. While ground measurements provide precise and frequent observations (Webb et al., 2013; Curole, 2018), they are local point measurements, and their spatial coverage is limited, making it difficult to test the equilibrium state hypotheses across the delta. Satellite imagery can be used to track subaerial land growth over large areas (Syvitski et al., 2005; Wolinsky et al., 2010), but it cannot resolve elevation differences. Methods that indirectly infer elevation or elevation change from inundation frequency or vegetation are limited to marsh tops and are insensitive to subtle vertical changes (Smith et al., 2020; Carle & Sasser, 2016; Bevington et al., 2022). Because of storms and floods, there might be fluctuations in the equilibrium state, making it difficult to test hypotheses using measurements made over a single time period. A longer time period is needed that averages over these events, in addition to providing spatial coverage.

Here we show how repeat airborne lidar offers an opportunity to bridge these gaps by providing high-resolution measurements of subaerial ground elevation over large coastal lands that can penetrate vegetation canopies (Töyrä et al., 2003; Wheaton et al., 2009; Okay et al., 2019). We build on earlier studies that analyzed repeat lidar in the Wax Lake Delta (WLD) (Wagner et al., 2017), expanding the data catalog to five lidar surveys collected over 11 years. After introducing the field areas, we discuss our methods to remove water and vegetation returns, coregister the data, and use a local field station to parse elevation change, accretion, and subsidence. Next, we present results on ground elevation, accretion rates, and trapping efficiency of the delta. We compare the decadal

accretion rate as a function of a suite of spatial metrics that have been hypothesized to influence sediment supply and trapping: distance from the delta apex, distance from primary channels or island edges, local ground elevation, and mean NDVI as a metric for vegetation density. Finally, we use our observations to investigate whether the delta is tending towards a topographic steady state, and if so, it is one of a delta-wide uniform elevation, regions of different uniform elevations, or an equilibrium downstream gradient.

## **2 Study Area & Background**

Wax Lake Delta is a young, actively prograding delta that is minimally influenced by human intervention and is still surviving in the mostly sinking Mississippi deltaic complex (Couvillion et al., 2017) (Figure 1). WLD began receiving sediment after a channel, 90 m wide and 14 m deep, was dredged from the Atchafalaya River in 1942 (Fisk, 1952), such that it receives approximately 46% of the total Atchafalaya River flow, which it equates to 14% of the total Mississippi River flow (Allison et al., 2012; Sendrowski & Passalacqua, 2017). The islands of WLD originated as subaqueous mouth bars (Wellner et al., 2005). In 1973, WLD became subaerial after a major flood event (Roberts et al., 1997). WLD has a subaerial area of approximately 50 km<sup>2</sup> (Olliver and Edmonds, 2017) and a subaqueous area of approximately 82 km<sup>2</sup> (Shaw et al., 2016). It is composed of ~1-4m deep bifurcating primary channels (Shaw et al., 2016) with teardrop-shaped islands in between (Figure 1a). The islands widen and decrease in elevation downstream (Figure 1a) and are bounded by levees that are breached by secondary channels (Figure 1b).



**Figure 1.** Location and morphology of the Wax Lake delta (WLD), Louisiana, USA. (a) Elevation map (North American Vertical Datum of 1988, NAVD88, referenced to the GEOID18 geoid model) of Wax Lake deltaic islands based on the 2020 lidar survey, with the black star as the location of the WLD apex, and the gray shading representing the cumulative area covered by the five lidar surveys used in this study. In the colorbar, the intertidal-supratidal elevation (30 cm) is annotated, indicating the approximate regional mean high water (MHW) level (following Twilley et al., 2019), which marks the transition between regularly and less frequently inundated elevations. Also shown is the location of the Coastwide Reference Monitoring System (CRMS) station CRMS0479. (b) A close-up of Mike Island showing levees and a secondary channel. (c) Map of South

Louisiana showing its main rivers and the location of WLD. (d) Maximum weekly discharge (black) measured at Calumet station, LA (U.S. Geological Survey, USGS, gauge 07381590) ~18 km upstream of the WLD apex (outside of panel a), and mean weekly water surface elevation (blue), referenced to NAVD88-GEOID18 and measured at the CRMS0479 station. The red lines show the acquisition dates of the lidar surveys, and the red stars mark the major flood events in which discharge exceeded the 7000 m<sup>3</sup>/s threshold.

River discharge in WLD exhibits annual cycles, with a low-flow regime in fall and a flood in spring, with an average annual discharge of 3000 m<sup>3</sup>/s (Sendrowski & Passalacqua, 2017) (Figure 1d). Tides also influence the delta, with water-level oscillations of approximately 40 cm (Shaw & Mohrig, 2014; Hiatt & Passalacqua, 2015). During the study period, WLD experienced several hurricanes and storms, including Hurricanes Gustav and Ike in 2008, Tropical Storm Lee in 2011, Hurricane Isaac in 2012, Hurricane Harvey in 2017, Hurricane Barry in 2019, and Hurricanes Laura, Delta, and Zeta in 2020. If we consider the 98th percentile discharge as the threshold for major floods, at approximately 7000 m<sup>3</sup>/s, their occurrences during the study period were in 2008, 2011, 2016, 2018, 2019, and 2020 (Figure 1d; Bevington et al., 2017; Whaling and Shaw, 2020). The 2011 flood, in particular, expanded the delta by 5-6.5 km<sup>2</sup> (Carle et al., 2015), exceeding typical annual land growth rates observed in other intervals (e.g., Allen et al., 2012; Shaw et al., 2013). At the CRMS station near the delta apex (Figure 1d), water surface elevations oscillate mostly between -0.17 m and 0.87 m with a mean water level of 0.36 m, but can reach above 1 m (Smith et al., 2020).

Vegetation distribution in Wax Lake Delta is primarily controlled by inundation frequency and duration, which regulate oxygen availability, nutrient supply, acidity, and toxicity (Bevington et al., 2022; Mitsch et al., 2023). These inundation regimes are in turn governed by ground elevation relative to the tide, allowing deltaic lands to be classified into hydrogeomorphic zones (Twilley et al., 2019). In the Atchafalaya basin, these hydrogeomorphic zones are: subtidal (ground elevations below -4 cm), low-intertidal (-4 cm to 12 cm), high-intertidal (12 cm to 30 cm), and supratidal (elevations above 30 cm) (Twilley et al., 2019).

Vegetation distribution in WLD responds to this variability in inundation and varies seasonally, with high cover density from August to October and minimal cover density from January to March (Olliver and Edmonds, 2017). The dominant plant species occupy overlapping elevation ranges that can be broadly grouped into low- and high-elevation assemblages, separated at ~40 cm (Carle et al., 2015). The low-elevation group includes *Nelumbo lutea*, *Potamogeton nodosus*, and other submerged aquatic vegetation (SAVs), typically occurring within -1 to 31 cm ground elevations (+/- 1 standard deviation) with mean elevations of 7-21 cm (Carle et al., 2015). In contrast, the high-elevation group is mostly within the supratidal zone and includes *Colocasia esculenta* (elephant ear), *Salix*

*nigra* (black willow), and *Polygonum* spp. This group has mean ground elevations of 47-66 cm and spans 37 to 79 cm in ground elevation (+/- 1 standard deviation) (Carle et al., 2015). Above-ground and below-ground biomass production in WLD also varies with ground elevation, with optimal productivity in the high-intertidal and supratidal zones (Bevington & Twilley, 2018; Smith et al., 2020; Jensen et al., 2022).

There has been a substantial amount of previous work measuring accretion rates or elevation changes in Wax Lake Delta, including point measurements, remote sensing using imagery and lidar, and numerical modeling. Point measurements with feldspar-horizon markers are the most direct method of measuring accretion rates in WLD. The primary monitoring station in WLD for accretion is the CRMS station, ~3 km from the WLD apex (Figure 1a). The average accretion rate based on measurements reported at this station from February 2009 to March 2022 was approximately  $4.17 \pm 2.28$  cm/year (CPRA, 2022). Twilley et al. (2022) also measured accretion using stations distributed across the hydrogeomorphic zones on Mike Island (Figure 1b) between October 2019 and April 2023, and found a similar average rate of  $4.62 \pm 2.42$  cm/year. Using their zone classifications, we calculated average rates of 4.57 cm/year in the subtidal zone, 6.07 cm/year in the intertidal zone, and 3.30 cm/year in the supratidal zone (Twilley et al., 2022). These magnitudes suggest that accretion is highest in intertidal, followed by supratidal, and subtidal zones.

In addition to accretion variability across hydrogeomorphic zones, Ma et al. (2018) found that mean elevation change varied substantially among vegetation classes using lidar differencing from 2009-2013. While remote sensing from imagery and lidar can be used to measure land elevation changes, it is not a direct measure of accretion because of shallow subsidence. Ranked from the vegetation classes occupying the highest ground elevations to the lowest, they found that the mean rates of elevation change were: *Salix nigra* (0.15 cm/year), *Colocasia esculenta* (1.20 cm/year), *Polygonum* spp. (1.54 cm/year), *Eichhornia crassipes* (1.48 cm/year), *Nelumbo lutea* (2.87 cm/year), *Potamogeton nodosus* (4.46 cm/year), SAVs (3.13 cm/year), and Water/Other (4.66 cm/year) (Ma et al., 2018).

Due to the difficulty of measuring accretion within vegetation, other studies have turned to numerical models. Numerical simulations (Delft3D) in WLD showed that introducing vegetation as elements of bed roughness induced deposition on deltaic lands (Nardin et al., 2016). However, when vegetation density was further increased, the resulting increase in flow resistance caused the discharge to divert into channels. In contrast, a numerical model by Olliver et al. (2020) using Delft3D found that intermediate vegetation density caused flow diversion back into channels more than it contributed to trapping. Only with large discharge values ( $\geq 8000 \text{ m}^3/\text{s}$ ), which are not very common in WLD, did they observe trapping exceeding diversion (Olliver et al., 2020). Vegetation can also impact bottom shear stress from waves and affect reentrainment and long-term

accretion (Styles et al., 2021). Ultimately, the model results for mud accretion are uncertain due to flocculation and unconstrained mud-transport physics (Nghiem et al., 2022). These findings prompt an investigation into whether delta accretion increases with vegetation density, or not, or whether it is maximized at intermediate density.

In addition to variability with ground elevation and vegetation, accretion in WLD varies through time and depends on the averaging window over which it is measured. Mean accretion rates averaged in the CRMS in (2009-2022; CPRA, 2022) are similar to those averaged over shorter intervals (2019-2023; Twilley et al., 2022). However, shorter-term measurements can capture substantially higher rates. For example, Styles et al. (2017) reported considerably high accretion rates over a six-month period beginning in January 2014, with rates of ~8.92-8.97 cm/year near the island edge and up to ~30.2 cm/year farther within Mike Island. Likewise, using multiple laser elevation transects across several islands between 2008 and 2011, Bevington et al. (2017) found that flood events in 2008 and 2011 had large elevation gains of about 5-15 cm. Due to these events, it is important to average over many years or decades to recover long-term trends.

There is also substantial variability of accretion within deltaic islands. For example, along the western levee of Pintail Island between October 2011 and April 2012, Delaune et al. (2016) recorded little to no accretion closer to the island apex, while they measured ~3-4 cm/year at stations further downstream. At a later time period (2019-2020), Fontenot (2022) observed two opposing downstream trends in Mike Island. Closer to the island apex, the supratidal station recorded an accretion rate of 4.31 cm/year, similar to the subtidal station, which recorded a rate of 4.43 cm/year. However, accretion rates increased downstream in the supratidal station to 7.06 cm/year, while they decreased to only 2.62 cm/year in the subtidal station (Fontenot, 2022). Land building is also variable with distance from island edges. For instance, Olliver & Edmonds (2017) found that levees had an elevation change rate of ~6.8 cm/year, whereas island interiors had a much lower average rate of ~2.3 cm/year. Smith et al. (2020) calculated marsh-top elevations from water levels and Landsat imagery, and found that elevation gains were concentrated where levees expanded laterally downstream from island apices, and elevation losses occurred in island interiors.

In terms of changes down delta, Bevington and Twilley (2018) used subaerial exposure maps between 1974 and 2012, and showed that upstream regions became subaerial first in WLD (Bevington & Twilley, 2018), indicating higher elevation gains upstream compared to downstream. In comparison, with a time series of Landsat imagery in WLD (1984-2015), Olliver and Edmonds (2017) found that areas closer to the WLD apex required more time to transition to supratidal, ~20 years, compared to ~10 years at distal lands. These studies suggest that the locus of accretion may have shifted from upstream to downstream as WLD evolved. This idea is consistent with Wagner et al. (2017), who differenced lidar surveys (2009-2013) and found that elevation gains

increased downstream on average. As such, the downstream topographic gradient decreased from  $-8.1 \times 10^{-5}$  m/m in 2009 to  $-5.8 \times 10^{-5}$  m/m in 2013 (Wagner et al., 2017). Wagner et al. (2017) suggested that this flattening resulted from upstream regions being too high to experience frequent inundation with coarse-grained, sediment-rich flows. They proposed that the coupling of accretion with water surface elevation would drive the delta to a uniform equilibrium elevation, consistent with the constant elevation hypothesis. The equilibrium elevation was proposed to be  $\sim 56$  cm, and the time to steady state was estimated at  $\sim 16$  years (Wagner et al., 2017). Alternatively, Smith et al. (2020) suggested that the delta produces a persistent downstream topographic gradient of  $1\text{--}1.2 \times 10^{-4}$  m/m, but within that gradient are platforms that maintain stable elevations at  $\sim 30$  cm,  $\sim 20$  cm,  $\sim 40$  cm, and  $\sim 90$  cm ground elevations.

Building on the study of Wagner et al. (2017), here we investigated the spatial and temporal variability of accretion using an expanded lidar dataset (2009, 2011, 2012, 2013, and 2020). By examining the elevation zones and downstream topographic gradients, we tested whether WLD was at quasi-equilibrium over the study period and which conceptual model better describes this topographic steady state. We also evaluated some of the various metrics that previous work had identified as controls on local accretion rates: vegetation, ground elevation, distance from the island apex, distance from island edges, and distance from the delta apex.

### 3 Methods

#### 3.1. Lidar Surveys and Definition of Elevation Change

The lidar surveys used in this study span 11 years (2009-2020) and were acquired and processed by multiple agencies using different horizontal and vertical references (Table 1). For each survey, we compiled the reported vertical uncertainty and calculated point density and subaerial land coverage (Table 1). The combined spatial footprint of the five lidar surveys primarily covers the frequently exposed levees and island margins, whereas most island interiors were not consistently sampled (Figure 2a). Consequently, our analyses focus on regions that were captured in all five surveys, or in the 2009 and 2020 acquisitions. This overlap region corresponds to areas that are almost always subaerial based on the cumulative Landsat-derived water non-exceedance probability map (Figure 2b; see Section 3.7). The water non-exceedance map shows the probability of water exceeding the marsh-top elevation based on a Landsat imagery analysis (See Section 3.7).

**Table 1.** General information on the different lidar surveys, including their point density and vertical accuracy.

| Acquisition Date    | Point density (pt/m <sup>2</sup> ) | Vertical uncertainty (cm) | Horizontal Reference | Vertical Reference | Land coverage area (km <sup>2</sup> ) | Source                           |
|---------------------|------------------------------------|---------------------------|----------------------|--------------------|---------------------------------------|----------------------------------|
| 14-15 January 2009  | 2.03                               | 5.5                       | NAD83 (CORS)         | NAVD88 (GEOID 3)   | 42.7                                  | NCALM, OpenTopography            |
| 22 January 2011     | 0.91                               | 19.4                      | NAD83 (2011)         | NAVD88 (GEOID 18)  | 47.9                                  | USGS, NOAA                       |
| 18 December 2012    | 2.04                               | 8.6                       | NAD83 (2011)         | NAVD88 (GEOID 18)  | 104.4                                 | USGS, NOAA (NOAA, 2015)          |
| 13-14 February 2013 | 11.67                              | 5.5                       | WGS84                | NAVD88 (GEOID 12A) | 26.2                                  | NCALM, UT Austin, OpenTopography |
| 16 November 2020    | 19.16                              | 1.3                       | NAD83 (2011)         | NAVD88 (GEOID 18)  | 27.9                                  | NCALM, Caltech, (Nghiem, 2022)   |

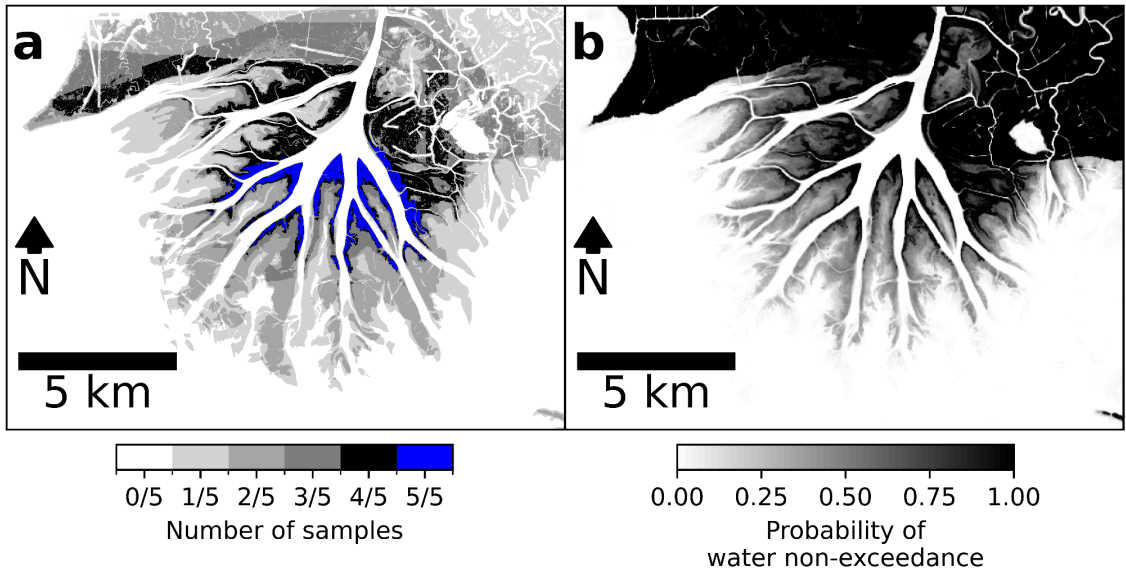


We defined lidar-derived ground elevation change, expressed under a mass-balance framework, as:

$$\Delta z_{Lidar} = A - SS - DS + \epsilon \quad (1)$$

The elevation change  $\Delta z_{Lidar}$  [L] calculated between a pair of lidar surveys is influenced by several factors (Equation 1). The accretion thickness  $A$  [L] is defined as the net thickness of deposition or erosion of organic and mineral sediment between surveys, plus pore spaces. In addition to sediment flux and local organic production, the accretion amount is influenced by the compaction of sediment that accumulated since the previous survey. The shallow subsidence  $SS$  [L] represents elevation loss in the shallow layers below the newly accreted sediment.

Deep subsidence  $DS$  [L] and systematic error  $\epsilon$  [L] typically produce spatially uniform elevation shifts at the delta scale. Deep subsidence reflects compaction of older and deeper deposits and regional tectonics, whereas systematic errors arise from calibration of lidar return to GPS stations. The boundary between shallow and deep subsidence is generally methodological. GPS stations are typically anchored at depths greater than ~15 m to track regional ground offsets caused by the compaction of deeper layers (Jankowski et al., 2017). Shallow subsidence is assumed to be influenced by actively accreting layers at the upper 5-10 m of Holocene deposits (Jankowski et al., 2017; Nienhuis et al., 2017). Because we assumed both deep subsidence and systematic error were constant across the study area, spatially uniform vertical co-registration was applied to eliminate their effect.



**Figure 2.** (a) Lidar acquisition overlap map of the five lidar surveys; white regions indicate no land was subaerial during any lidar acquisition, while blue regions were subaerial during the acquisition of all five lidar surveys. (b) Water non-exceedance probability map (Section 3.7) compiled from Landsat images between the acquisition of the first and last lidar survey (Table 1); white shading indicates areas almost always submerged under water, while black shading indicates areas almost always subaerial.

### 3.2. Vertical Co-registration

To ensure accurate calculations of elevation change between lidar surveys, we first transformed all datasets into a common reference frame. Surveys not originally referenced to NAD83 (horizontal) and NAVD88-GEOID18 (vertical) (Table 1) were transformed using NOAA VDATUM software.

Next, to minimize vertical systematic error,  $\epsilon$ , we applied vertical shift corrections using six stable reference structures distributed across WLD (e.g., water tanks and oil and gas platforms; Figure 3a). These structures were selected based on the absence of visible modification in historical Google Earth imagery (2009-2020). A similar approach was applied by Wagner et al. (2017), using four of the structures.

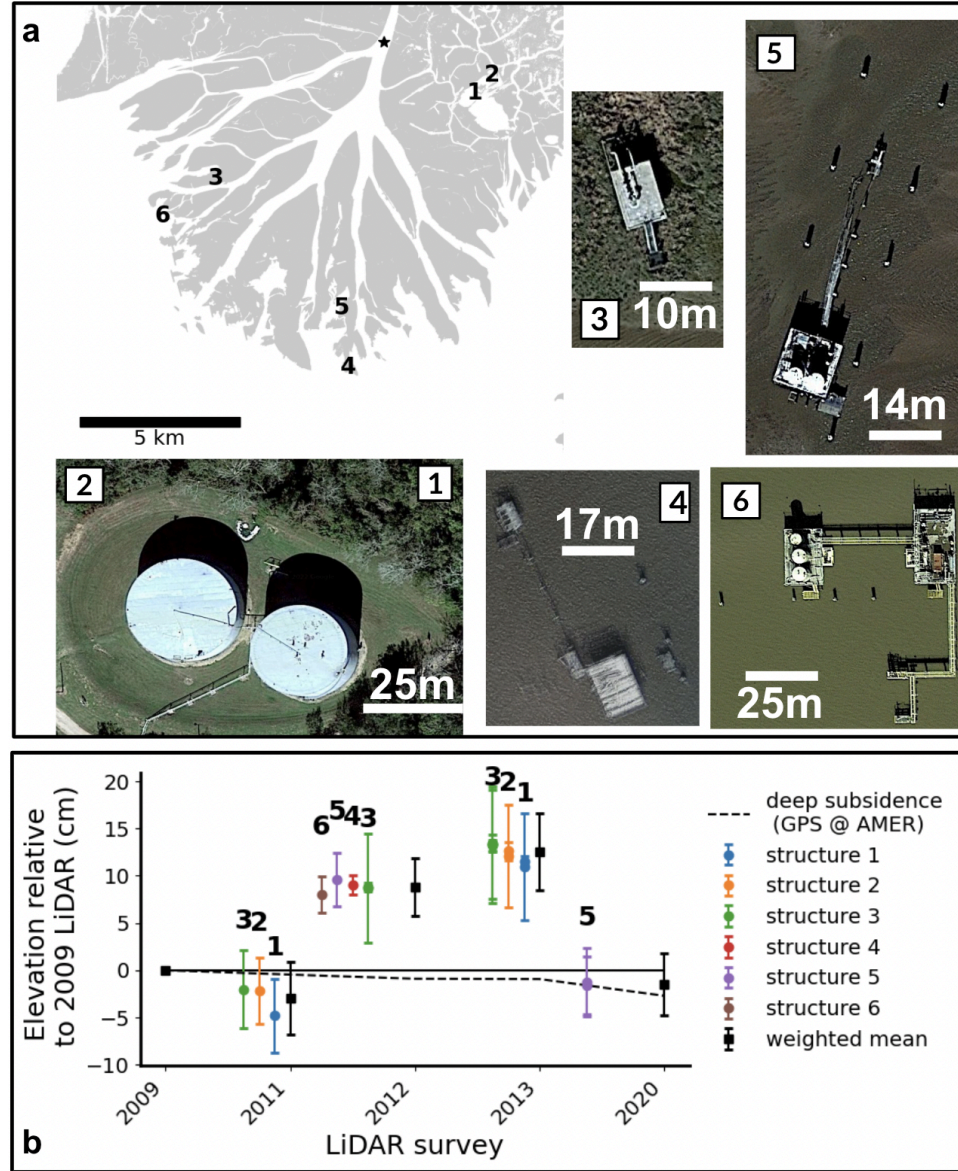
We used the multiscale model-to-model cloud comparison (M3C2; Lague et al., 2013) tool in CloudCompare (CloudCompare, 2024) to calculate pointwise elevation differences at the reference structures for each lidar survey pair in which the structures were resolved. We used a 0.5 m projection depth and 10 m search diameter. An unsupervised outlier detection algorithm (Isolation Forest) was applied to exclude anomalous elevation differences, which were typically at structure edges. For each structure and lidar pair, we calculated the mean and standard deviation of the filtered elevation differences. The mean offsets were then applied as vertical corrections to co-register each lidar survey to the 2009 lidar since it contained returns from all structures within its survey. For structures resolved in multiple survey pairs, we verified consistency by comparing cumulative offsets from consecutive lidar pairs with direct offsets computed between the first (2009) and later surveys (2012, 2013, and 2020).

In the co-registration workflow, we assumed that the high-elevation structures experienced no sediment deposition and that the underlying substrate was sufficiently consolidated, minimizing the contribution of accretion and shallow subsidence. Under these assumptions, any remaining local bias was expected to be small relative to measurement uncertainty. To verify that benchmark-specific bias related to structure size or construction history was minimal, we tested whether mean elevation differences across the six structures (computed for the same lidar pair) varied substantially. Differences between structures were within one standard deviation of the pointwise

elevation-difference distributions (Figure 3b), indicating that offsets were spatially consistent across benchmarks. This consistency allowed us to use the structure-based elevation differences to compute weighted vertical co-registration offsets for each survey (Figure 3b). The mean elevation differences,  $\Delta z_{Lidar}$ , represent the combined global offset caused by deep subsidence and systematic error ( $-DS + \epsilon$ ; Equation 1). Moreover, the deep subsidence rate recorded at the Amerada Pass GPS station (approximately -2mm/year; Abdalla et al., 2024), located ~13.5km SE from the WLD apex, is small relative to the vertical uncertainty of the derived co-registration offsets (Figure 3b).

We initially computed weighted mean offsets relative to the 2009 survey, which included returns from all six structures. Offsets were subsequently re-referenced to the 2020 lidar, which was assumed to provide the highest absolute elevation accuracy due to its recent acquisition, high point density, low uncertainty, and lack of spatial reference transformation.

The final vertical co-registration corrections applied relative to the 2020 lidar survey were  $-1.5 \pm 3.6$  cm (2009),  $1.5 \pm 4.9$  cm (2011),  $-10.3 \pm 4.5$  cm (2012), and  $-14.0 \pm 5.1$  cm (2013) (Figure 3b). Only vertical co-registration was performed because insufficient points were available to robustly constrain horizontal offsets. Potential lateral misalignment was not explicitly corrected, but its effect on vertical differencing is expected to be small. This is because we later used 5 m diameter to calculate point-wise ground elevation differences and 2 m x 2 m (4 m<sup>2</sup>) resolution to create the maps for analysis.



**Figure 3.** (a) Locations of the benchmark structures used for vertical co-registration, shown on Google Earth images. (b) Co-registration lengths of the six benchmark structures relative to 2009 lidar, with error bars. For comparison, the cumulative amount of deep subsidence calculated from GPS station data (Abdalla et al., 2024) at Amerada Pass, ~13.5 km SE of the WLD apex, is shown as a dashed black line. Colored error bars indicate the mean and standard deviation of elevation differences at each available structure for each lidar year relative to 2009. The black error bars show the co-registration lengths as weighted means based on all the individual mean elevation residuals at each year relative to 2009. For several structures of a specific lidar year after 2011, both the summed means of elevation differences of the consecutive inter-annual

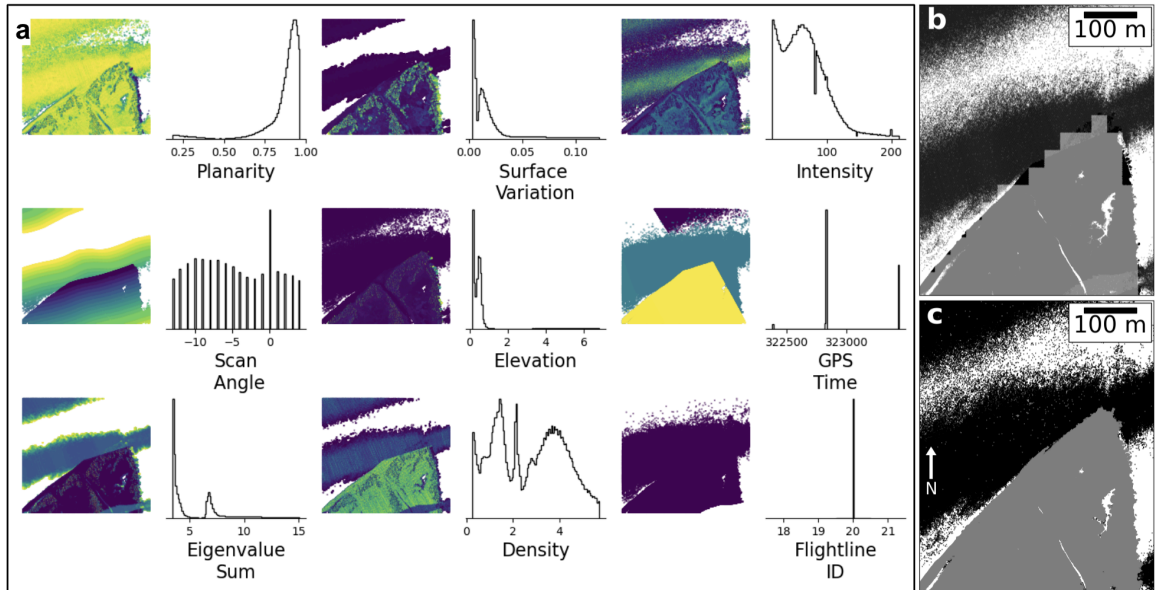
lidar pairs and the mean of direct elevation differences between 2009 and that specific lidar year (2012, 2013, and 2020) are shown; their close agreement supports the reliability of the co-registration results across all structures.

### *3.3. Removing Water Returns and Flightline Misalignments*

Because the 2009 survey was not initially filtered for water returns, unlike the other surveys, we developed a custom classification workflow. This workflow was necessary because infrared laser pulses in the 2009 survey produced detectable returns over turbid water surfaces (Shaw et al., 2016), rather than yielding no returns as typically expected for open water. As an initial step, we applied an NDVI-based land mask derived from a Landsat image acquired on January 12, 2009 (Table 1). However, because the Landsat mask has 30 m resolution, this procedure produced jagged land-water boundaries (Figure 4b).

To refine the classification, we trained a supervised learning approach using the eXtreme Gradient Boosting algorithm (XGBoost; Chen & Guestrin, 2016). In addition to lidar point attributes (e.g., intensity, elevation, and flightline ID), we incorporated neighborhood-based covariance (dimensionality) features computed using the Point Data Abstraction Library (PDAL; Butler et al., 2021; PDAL contributors, 2022). These features (e.g., scattering, linearity, planarity, and local point density) were derived from eigenvalue-based metrics computed from principal component analysis of local point neighborhoods (Figure 4a). We used the NDVI-derived mask as weak training labels to train the XGBoost classifier. The resulting classification produced substantially improved separation between water and land returns compared to the Landsat mask alone (Figure 4c). Finally, we applied a neighborhood-based post-processing filter to remove isolated misclassifications.

In addition to removing water returns from the 2009 survey, the 2012 survey required additional processing because it was acquired over an extended period spanning several months. We leveraged GPS timestamps to isolate subsets captured at WLD on the same day (Table 1). Additionally, in the 2013 survey, significant misalignments were observed among flight lines, particularly at their edges, likely attributed to high scan angles. We improved alignment across flight lines by calculating elevation differences within overlap zones and filtering out points with large vertical offsets.



**Figure 4.** Supervised classification of water/land returns in 2009 lidar. (a) The lidar parameters and neighborhood-based dimensionality features used for training/classification, shown for each parameter/feature as both property maps and density histograms. The value scales of the histograms are the same as the color scales of the property maps. (b) Lidar returns at the apex of Mike Island shaded using the Landsat-based water mask. Gray points in b and c are classified as land returns, black points are classified as water returns, while the white space had no data. (c) Same lidar returns as in panel b but classified using the Extreme Gradient Boosting (XGBoost) classifier trained on the features in panel a.

### 3.4. Removing Low-Lying Vegetation

The final phase of lidar data processing involved removing vegetation, in particular low-lying vegetation, using a custom workflow. The workflow was designed to avoid issues reported in previous studies, such as inadvertent levee decimation, as noted by Wagner et al. (2017). To mitigate this issue, our approach excluded returns located at bank edges, ensuring these were not misclassified as ground points. For this purpose, we calculated the “Verticality” attribute using the PDAL library to identify and remove returns forming locally vertical clusters with neighboring points. This method effectively removed the edges of banks, shrubs, and tree trunks.

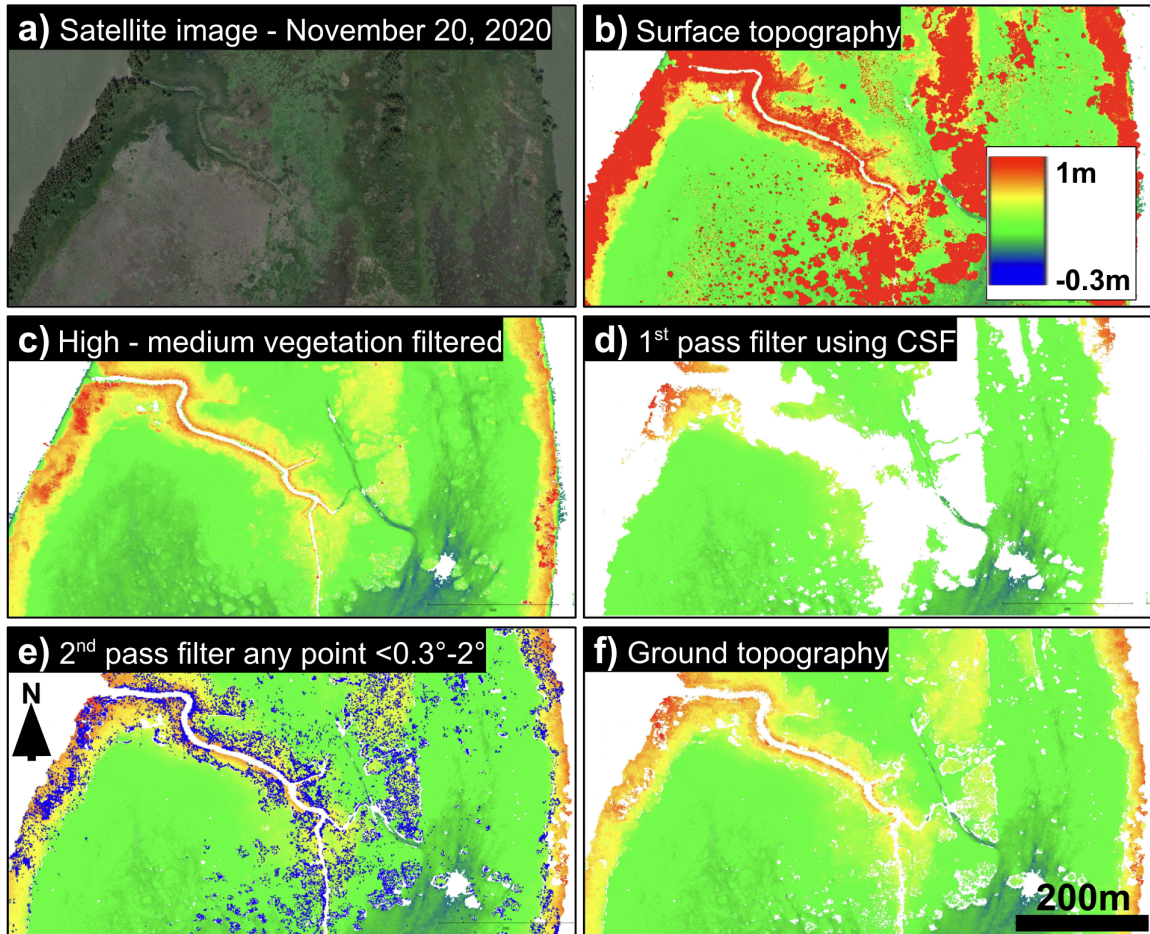
Furthermore, several studies have raised issues about the vertical accuracy of lidar-derived ground elevations in coastal environments (Töyrä et al., 2003; Schmid et al., 2011; Hladik and Alber, 2012). In addition to the inherent vertical uncertainty of lidar

returns, the high vegetation density typical of coastal landscapes often results in poor laser penetration. Moreover, the short height of herbaceous emergent vegetation provides insufficient relief to reliably distinguish vegetation returns from ground returns. Fortunately, most lidar surveys used in this study were acquired during the winter season when vegetation is senesced and largely reduced (Table 1). In addition, the 2020 survey was preceded by Hurricane Laura, which likely removed much of the low-lying vegetation cover (Carle et al., 2015; Carle et al., 2016; Bevington et al., 2022).

To further filter ground returns, we applied an aggressive custom workflow. First, we used the Cloth Simulation Filter (CSF; Zhang et al., 2016), which simulates a cloth with a specified rigidity draped over the inverted landscape to identify returns exceeding a threshold distance from the simulated surface (Figure 5d). Given the variability in point densities across surveys, we used different grid resolutions for each dataset: 50m for 2011, 30m for 2009 and 2012, and 10m for 2013 and 2020. The coarse cloth resolution was intended to capture only broad-scale topography and retain returns most likely to represent ground elevations (Wang et al., 2009). In addition, the distance threshold from the simulated cloth was set to 10 cm for 2011 and 6 cm for the remaining surveys. The CSF tool we used in CloudCompare also proved effective at detecting relatively low points, classifying them as non-ground.

Our CSF parameterization classified many points as non-ground, including returns located over levees and overbank deposits, which are expected to have relatively dense and tall vegetation (Olliver and Edmonds, 2017). To correct for misclassified ground returns, we incorporated additional reclassification steps. We calculated the local relief and the distance of each point relative to its nearest neighbors, and from these values we derived the local slope angle for each point. Using both slope angle and height above the locally lowest neighboring points, we progressively reclassified points initially filtered out by the aggressive CSF settings. This reclassification used a height threshold of 5 cm for 2011 and 3 cm for the remaining surveys, and gradually increasing slope-angle thresholds of 0.3°, 0.5°, 1.0°, and 2.0° (Figure 5e-f).





**Figure 5.** An example of the steps of the low-lying vegetation filtering workflow. (a) Google Earth satellite image of a segment of Mike Island acquired on November 20, 2020, several days after the acquisition of the 2020 lidar survey in the remaining panels (b-f). (b) Elevation map from the 2020 survey at the same location as in (a). (c) After removing high and medium relief vegetation (trees and shrubs) identified by the acquisition/processing agencies. (d) After applying the cloth simulation filter (CSF) with aggressive settings, removing returns with almost any relief higher than 10 cm (e.g., most levees). (e) A second-pass filter where returns that were filtered in (c) are gradually reclassified as ground, starting with a  $0.3^\circ$  threshold, then  $1^\circ$ , then  $2^\circ$ ; remaining points are in blue (e.g., low-lying shrubs). (f) Elevation map with only returns classified as ground remaining. Color in panels (b-f) indicates elevation, while white space indicates “no data” or was flagged as water/noise.

### 3.5. Field Measurements of Elevation, Elevation Change, and Accretion



We compiled ground-based measurements of elevation, elevation change, and accretion collected in WLD during the study period from different sources (Bevington et al., 2017; Olliver & Edmonds, 2017; Rovai et al., 2022; Twilley & Rovai, 2022; CPRA, 2022; Twilley et al., 2022). Absolute elevation data include repeated laser-level surveys along fixed transects (2008-2011; Bevington et al., 2017) and RTK-GPS surveys collected at additional locations (Olliver & Edmonds, 2017; Rovai et al., 2022; Twilley & Rovai, 2022; Twilley et al., 2022). We also collected absolute elevation measurements with a Trimble R12 GPS unit in March and August 2021 (Table S1 in Supporting Information S1).

Point measurements of accretion and elevation change were also collected at a continuous monitoring station, CRMS0479, located ~3km SW from the WLD apex (Figure 1a) by the Coastal Protection and Restoration Authority (CPRA) as part of the Coastal Reference Monitoring System (CRMS). At this CRMS station, the rod surface elevation table (RSET) method is used to measure ground elevation (CPRA, 2022) relative to a deep benchmark rod. The rods were driven into Holocene sediments until resistance was met, and anchored at depths, which were estimated to be  $22.9 \pm 6.3$  m (Jankowski et al., 2017), and are similar to those of GPS stations (>15 m; Jankowski et al., 2017). Also, at the same CRMS station, accretion data were measured with feldspar marker horizons (CPRA, 2022). Accretion amounts are collected using cryocores and measured as the sediment thickness above white feldspar-horizon markers distributed across several plots at each station. Other studies have collected accretion data using the same method at different locations in WLD, mostly on Mike Island (Figure 8a; Twilley et al., 2022), as part of the NASA Delta-X project archived in their ORNL DAAC Delta-X database.

To calculate accretion from these datasets, we measured accretion amounts between measurement surveys and divided them by the time between those surveys. We used different temporal averaging intervals over a series of consecutive surveys, allowing us to include measurements of erosion and elevation loss (Figure 6). We excluded elevation change records that required reference resets (e.g., rod-collar elevation adjustments). At CRMS0479, such a reset was required following Hurricane Barry (July 2019), which deposited up to ~51 cm of sediment above some feldspar horizon marker and produced ~38 cm of elevation gain at the RSET station.

To compare the elevation change during the study period with the semi-centennial rate of elevation change in WLD, we subtracted the bathymetry data collected in 1934-1935 from the 2009 lidar elevation map. Since WLD was not dredged until 1941, we assumed that the bathymetry data represented the initial topography of WLD starting on January 1, 1942. The bathymetry sounding data were compiled by NOAA, with horizontal and vertical resolution of 30 m and 10 m, respectively (Shaw et al., 2013), and were

referenced to the mean lower low water (MLLW) vertical datum. We assumed that the datum transformation from MLLW to NAVD88 GEOID18 for NOAA bathymetry data within WLD could be approximated by a spatially uniform offset. This offset was calculated using the NOAA VDATUM tool to be -0.286 m, which we subtracted from the bathymetry data.

To investigate the association between ground elevation and water inundation, we also analyzed the water-level time series from the CRMS0479 station to find the water level distribution (Figure 1d). In addition, we used water-surface elevation data measured using AirSWOT Ka-band interferometry (Denbina et al., 2023) to find delta-averaged downstream water surface elevation profiles. The measurements were collected simultaneously across the primary channels of WLD on March 26 to April 2, 2021, during the high-flow regime in spring, and from August 21, 2021, to September 12, 2021, during the low-flow regime in fall (Denbina et al., 2023).

### *3.6. Measuring Elevation Change and Estimating Accretion and Trapping Efficiency*

We quantified elevation change between lidar surveys using the vertical version of M3C2 (Lague et al., 2013) in CloudCompare (CloudCompare, 2024). Although conceptually similar to the “Difference of DEMs” method, M3C2 calculates elevation differences directly at the point level prior to gridding, allowing pointwise vertical uncertainty to be estimated from local point-cloud statistics (Lague et al., 2013). For each point, M3C2 identifies neighboring returns within a 5 m diameter window and calculates the mean elevation, standard deviation, and number of contributing points ( $N$ ). The same neighborhood extent is applied in the subsequent survey, and pointwise elevation change is computed as the difference between the two neighborhood means. To ensure statistical robustness, we discarded elevation-change measurements with fewer than four contributing points, consistent with the convention that both lidar elevation and elevation change estimates require at least four returns (Lague et al., 2013).

To estimate vertical uncertainty, the standard deviation of elevation ( $\sigma_z$ ) at each point was adjusted to account for the number of contributing points ( $N$ ) and the inherent vertical uncertainty ( $\epsilon_z$ ) derived from GPS calibration (Table 1). Using these terms, we calculated the adjusted standard deviation for each survey pair (Equation 2). The total vertical uncertainty associated with each pointwise elevation-change estimate was then computed using Equation (3), Wagner et al. (2017). This formulation incorporates both co-registration uncertainty ( $\sigma_{\text{registration}}$ ) and the correlation coefficient ( $r$ ) between the standard deviations of the two surveys. Estimated pointwise uncertainties ranged from 3.5 cm for high-density lidar surveys and 9.5 cm for low-density surveys, with the largest

vertical uncertainties associated with elevation differences involving the 2011 survey (Table 1).

Following pointwise differencing, lidar elevation, elevation change, and total vertical uncertainty values were interpolated using inverse distance weighting onto structured grids with 2 m spatial resolution. Gridded maps were generated over an area of interest spanning UTM coordinates 637,950 E to 662,050 E and 3,251,950 N to 3,271,050 N.

$$\sigma_1 = \sqrt{\frac{\varepsilon_{z1}^2 + \sigma_{z1}^2}{N1}} \quad \sigma_2 = \sqrt{\frac{\varepsilon_{z2}^2 + \sigma_{z2}^2}{N2}} \quad (2)$$

$$\varepsilon_{\Delta z_{Lidar}} = \sqrt{\sigma_1^2 + \sigma_2^2 + \sigma_{registration}^2 - 2r\sigma_1\sigma_2} \quad (3)$$

As an additional step of validating absolute elevation measurements, we tested two methods. First, we tested minimum bin-gridding, whereby the minimum lidar return within each grid cell is used instead of the inverse-distance-weighted average elevation and compared with field measurements of elevations (Schmid et al., 2011; Medeiros et al., 2015). Using the average lidar elevation yielded an absolute mean residual of 13.22 cm, whereas using the minimum lidar elevations reduced the absolute mean residual to 12.45 cm, producing only a marginal improvement. Second, we tested whether increasing the interpolation diameter could reduce the bias from vegetation (Wang et al., 2009). However, expanding the interpolation diameter up to 20 m and selecting the lowest lidar return did not improve residual statistics.

Following co-registration, lidar-derived elevation change does not directly represent accretion because vertical change also reflects shallow subsidence (Equation 1; Cahoon et al., 1995; Jankowski et al., 2017; Lynch et al., 2015). To separate shallow subsidence from elevation changes and derive accretion rates, we analyzed concurrent field measurements of accretion and elevation at the CRMS0479 station (Figure 1a; CPRA, 2022). Shallow subsidence was calculated as the difference between measured accretion and measured elevation change (Equation 1; Cahoon et al., 1995; Jankowski et al., 2017). This difference is attributed to shallow subsidence because feldspar marker horizons measure sediment accumulation above the marker surface and are not influenced by subsidence. Additionally, although deep subsidence affects both surface elevation and rod-collar elevation, RSET-derived elevation change should not be affected by deep subsidence.

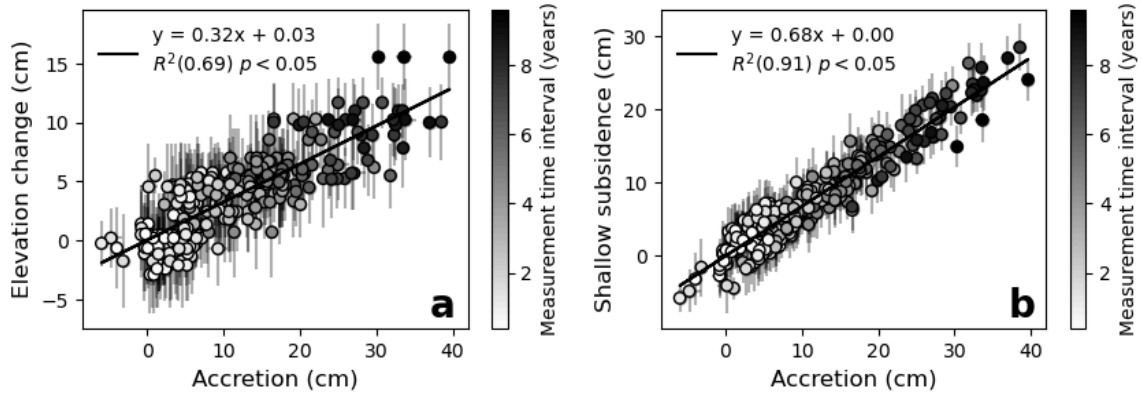
Field measurements revealed that shallow subsidence exhibited a strong linear relationship with accretion (Figure 6b). This relationship indicates that elevation loss below the feldspar marker horizon scales proportionally with the amount of accretion above the horizon, with shallow subsidence accounting for approximately 68% of the

accretion thickness. Shallow subsidence is controlled by multiple factors (e.g., grain size packing, hydraulic conductivity, organic matter compressibility, etc.). However, in fully saturated fresh sediments, the dominant mechanism is porosity loss by pore-water expulsion under sediment loading (Törnqvist et al., 2008; Asselen, 2011; Nienhuis et al., 2017; Jankowski et al., 2017; Valencia et al., 2023). Previous studies indicate that compaction is concentrated within the upper ~3-4 m of newly deposited sediments over relatively short timescales (Törnqvist et al., 2008; Nienhuis et al., 2017; Keogh et al., 2021). The strong fit of the observed relationship ( $R^2 > 0.9$ ) suggests that the proportionality between accretion and shallow subsidence remained consistent over the measurement period (Figure 6b). This relationship may decay over longer timescales (Valencia et al., 2023). In addition, because organic matter represents approximately 10% of the deltaic sediment thickness (Smith, 2014), its contribution to sediment compressibility is likely minor relative to mineral sediment compaction (Cahoon et al., 1995). Similar proportional relationships between subsidence and accretion have been documented in other deltaic environments, with shallow subsidence accounting for up to ~40% of depositional thickness in some cases (Törnqvist et al., 2008; Asselen, 2011).

Based on the linear regression slope ( $0.68 \pm 0.01$ ) and intercept ( $0.00 \pm 0.19$ ) derived from CRMS0479 measurements (Figure 6b), we expressed shallow subsidence ( $SS$ ) as a fraction of accretion. By substituting this relationship into Equation (1), rearranging the terms, and accounting for the global co-registration offset, we derived accretion ( $A$ ) from lidar elevation change ( $\Delta z_{Lidar}$ ) as:

$$A = 3.125 \Delta z_{Lidar} \quad (4)$$

Because ground measurements of erosion were limited, Equation (4) was applied only to positive values of elevation change. Negative lidar elevation changes were interpreted as erosion and were not adjusted for shallow subsidence. This relationship is applied uniformly across the study area as a first-order approximation and a starting place for estimating accretion, acknowledging that compaction processes and shallow subsidence rates may vary spatially across the delta.



**Figure 6.** (a) Accretion versus elevation change and (b) Accretion versus shallow subsidence measured at CRMS0479 (Coastal Protection and Restoration Authority, CPRA, 2022). Values represent the medians and standard deviations of accretion (cm) and elevation change (cm) derived from the feldspar marker horizon plots and the rod surface elevation table (RSET) measurements. Data points are shaded by the time interval between measurements. Linear regression results indicate a strong proportionality between accretion and shallow subsidence.

The trapping efficiency ( $TE$ ) is a metric for evaluating sediment retention in a delta, which can be defined as the mass of sediment deposited on the subaerial lands compared to the total suspended sediment mass supplied by the river (Kim et al., 2009). To quantify trapping efficiency ( $TE$ ) in WLD, we used:

$$TE = \frac{\partial V / \partial t \rho_b}{Q_T \rho_s}, \quad (5)$$

in which the parameters are the lidar-derived volumetric accretion rate measured ( $\partial V / \partial t$ ), bulk sediment density ( $\rho_b = 1.14 \pm 0.22 \text{ g/cm}^3$ ; DeLaune et al., 2016), the total volumetric river suspended sediment discharge ( $Q_T$ ;  $\text{m}^3/\text{s}$ ) integrated over the same time period of lidar pairs, and the sediment density ( $\rho_s = 2.65 \text{ g/cm}^3$ ). We calculated suspended-sediment delivery using measurements from the nearest upstream monitoring station at Calumet, LA, assuming negligible sediment loss between Calumet and the WLD islands. Total volumetric sediment discharge ( $Q_T$ ; Equation 6) was computed as the sum of the mud discharge ( $Q_m$ ) and sand discharge ( $Q_s$ ), which in turn were fit to functions of water discharge ( $Q_w$ ;  $\text{m}^3/\text{s}$ ) (Wang et al., 2026):

$$Q_T = Q_s + Q_m \quad (6a)$$

$$Q_s = 7.86 \times 10^{-16} Q_w^{3.72} \quad (6b)$$

$$Q_m = 8.27 \times 10^{-10} Q_w^{2.37} \text{ for } Q_w < 4000 \quad (6c)$$

$$Q_m = 1.30 \times 10^{-3} Q_w^{0.62} \text{ for } Q_w > 4000 \quad (6d)$$

We calculated TE during three time intervals: the period encompassing the 2011 flood (2009-2013), the post-flood interval (2013-2020), and the full study period (2009-2020) to see the effect of floods. In addition, trapping efficiency was also calculated using two spatial extents. In the first approach, we used the overlapping subaerial area shared by all the lidar pairs (3.58 km<sup>2</sup>; Figure 2a). But of course, this is only a small area that receives sediment from the river. In the second approach, we used the full area of islands (51.73 km<sup>2</sup>; Figure 2a), which is similar to the previously estimated total subaerial area of WLD (50 km<sup>2</sup>; Olliver and Edmonds, 2017).

### *3.7. Deltaic Metrics Used to Compare to Elevation and Accretion*

To investigate variability in land building, we quantified the spatial patterns of elevation and accretion as a function of several geomorphic and remotely sensed metrics identified in previous studies. The analyzed metrics include ground elevation, downstream distance from the delta apex, downstream distance from individual island apexes, distance from the island edge, and mean NDVI and a preexisting classification map for vegetation metrics (Figure 7). In addition to these metrics we also explored accretion trends as a function of the radial angle relative to the WLD apex, and water non-exceedance probability (Figure 2b). Examining accretion as a function of the radial angle was meant to reveal if accretion varied laterally (i.e., west-east). The water non-exceedance probability approximates inundation frequency as the fraction of time a given marsh top remains above the water level. For each metric, we calculated linear correlations with the decadal accretion rates (2009-2020) using the Pearson correlation coefficient. These were used to rank the strength of linear correlations with accretion.

Downstream distance from island apex (Figure 7a) was calculated as the Euclidean distance from the upstream island tip. Distance from the WLD apex (Figure 7b) was calculated as the Euclidean distance of each grid cell from the WLD apex, located at UTM coordinates 652,230E and 3,269,100N (Wagner et al., 2017). The distance from island edges was calculated as the distance from manually drawn island borders. For ground elevation (Figure 7e), we used the 2009 elevation values. Radial angle was calculated as the counterclockwise Cartesian angle (degrees) using the WLD apex as the origin.

To derive mean NDVI and the water non-exceedance probability, we compiled Landsat imagery spanning the study period (2009-2020) and generated NDVI maps and corresponding binary land masks for each image. Mean NDVI was computed as the

pixel-wise average across all images. The water non-exceedance probability was calculated by averaging the binary land masks (Figure 2b). A total of 83 atmospherically corrected surface reflectance images from Landsat 5 and 8 were acquired using Google Earth Engine (Gorelick et al., 2017). Surface reflectance bands included blue, green, red, near-infrared (NIR), and shortwave infrared (SWIR1). These bands were used to calculate three indices: the normalized difference vegetation index (NDVI), the modified normalized difference water index (mNDWI), and the Enhanced Vegetation Index (EVI) (Equations 7-9).

To classify open water and generate binary land masks, we applied the method of Zou et al. (2018), combined with an NDVI threshold. Specifically, pixels were classified as open water when mNDWI exceeded NDVI or when mNDWI was lower than EVI. In addition, pixels with EVI less than 0.1 were classified as open water. We further classified any remaining land pixels with negative NDVI as open water.

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (7)$$

$$mNDWI = \frac{Green - SWIR_1}{Green + SWIR_1} \quad (8)$$

$$EVI = 2.5 \times \frac{NIR - Red}{(1 + NIR + 6 Red - 7.5 Blue)} \quad (9)$$

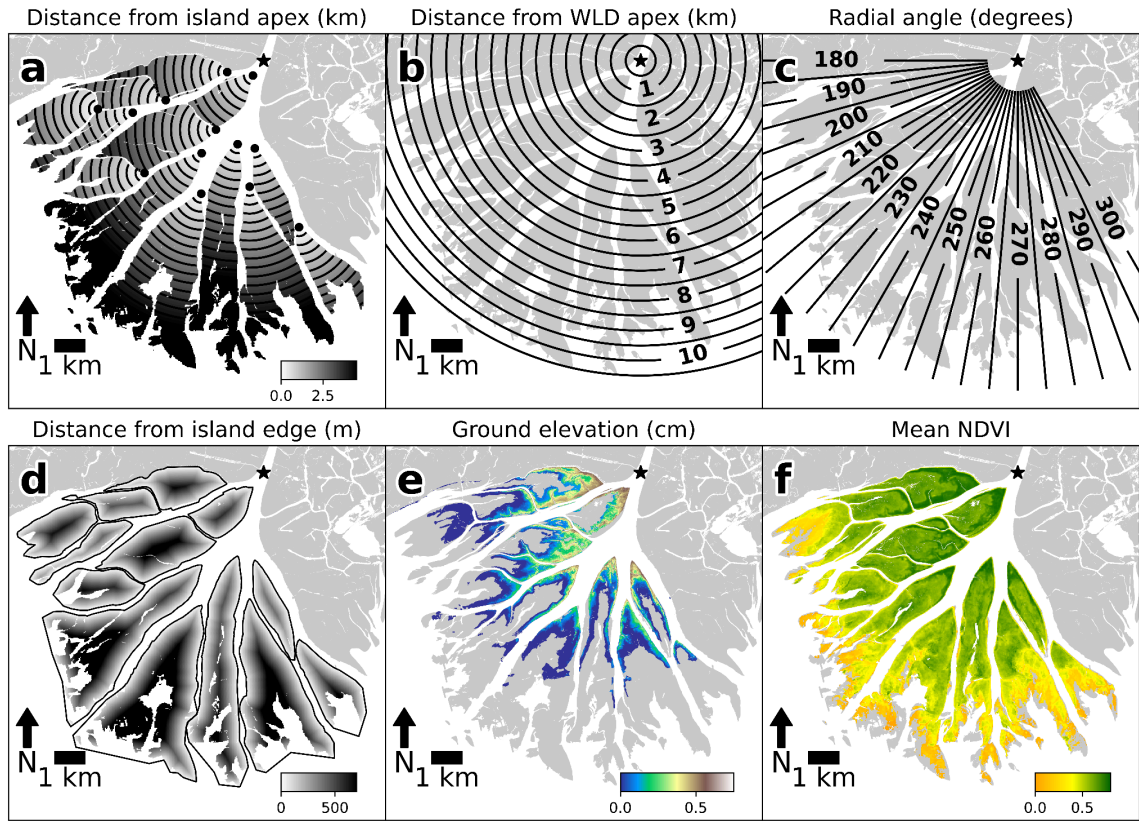
NDVI is widely used to quantify the presence and productivity of photosynthetic vegetation (Rouse et al., 1973) and has been extensively applied in coastal and deltaic environments, including WLD (e.g., Klemas, 2013; Nardin and Edmonds, 2014; Chenevert and Edmonds, 2024). In addition, NDVI is strongly correlated with the organic content in deltaic wetlands (Shields et al., 2017). When calculating mean NDVI for each grid cell, we included only values that were not flagged as water by the land masking workflow. Mean NDVI values can be influenced by seasonal phenology, inundation, saturation effects, and episodic disturbance such as vegetation removal during major floods and hurricanes (Medeiros et al., 2015; Carle et al., 2016; Bevington et al., 2022). However, integrating NDVI across more than a decade of imagery reduces the influence of short-term variability. Therefore, regions with high mean NDVI are interpreted as areas that remained vegetated during most of the study period, whereas low mean NDVI values represent persistently unvegetated or frequently inundated regions.

In addition to mean NDVI, we used a vegetation classification map of WLD that was derived from a hyperspectral satellite image, with 5.4 m resolution, acquired in October 17, 2016 (Accuracy = 77.62%; Jensen et al., 2021). Although the spatial extent of vegetation classes has varied (Carle et al., 2015; Jensen et al., 2021), we assumed the 2016 map represents approximately the spatial distribution of vegetation classes over the study period. Because both mean NDVI and water non-exceedance probability are

derived from time-integrated satellite observations, they may not be strictly independent of accretion and may partially reflect the cumulative effects of land building during 2009-2020.

It is worth noting that the metrics themselves are not independent of each other. Since the deltaic islands are higher upstream (Figure 1), the Pearson correlation coefficient is strongly negative between the distance from the WLD apex and the 2009 ground elevation ( $r = -0.66$ ), and between the distance from the WLD apex and water non-exceedance probability ( $r = -0.61$ ). The distance from island apexes also correlated with water non-exceedance ( $r = -0.47$ ) and ground elevation ( $r = -0.45$ ). Regions closer to the apex are higher and older (Bevington & Twilley, 2018), allowing them to have more established vegetation cover and, hence, higher mean NDVI ( $r = -0.53$ ). Mean NDVI also correlated with water non-exceedance ( $r = 0.63$ ), ground elevation ( $r = 0.38$ ), and the distance from island apex ( $r = -0.38$ ). In contrast, the distance from island edge is not correlated with mean NDVI ( $r = -0.05$ ), but is correlated with water non-exceedance ( $r = -0.49$ ) and 2009 ground elevation ( $r = -0.59$ ). Because of these correlations, the causality of accretion rate variance is hard to untangle. Our goal here is not to infer causality, but rather to test correlations between accretion and metrics that have been previously proposed.





**Figure 7.** An illustration of the various spatial metrics used for analysis. (a) The distance, in kilometers, from the apex of each island (black circles). (b) The distance from the WLD apex, in kilometers; the WLD apex is shown as a black star. (c) The radial angle, in degrees. (d) The distance from island edges, in meters, calculated from the manually drawn edges of each island (black polygons). (e) Ground elevation map, in centimeters. (f) Mean normalized difference vegetation index (NDVI), from 0 to 0.8, derived from Landsat image compilation, 2009-2020; only the values of mean NDVI that lie on the deltaic islands were included. The gray shading in all panels was generated by combining all lidar maps, which delineated regions that were subaerial during at least one lidar acquisition.

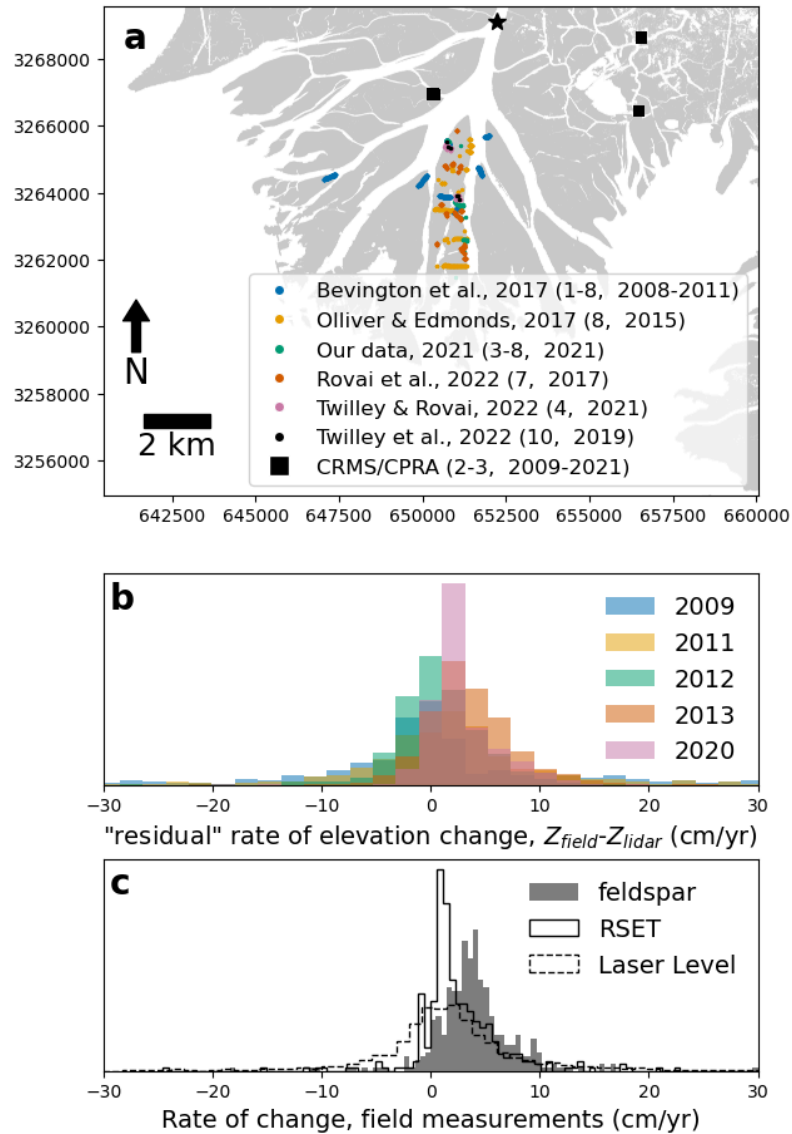
## 4 Results

### 4.1. Validation of Lidar Absolute Elevation

Before discussing the main results, we first show comparisons between the lidar and ground-based measurements at the locations where the ground-based measurements were made, for validation (Figure 8). Specifically, we calculated residual rates of

elevation change by dividing the elevation difference between each lidar elevation and its corresponding field measurement by the time interval separating their acquisition. Across all surveys, the mean residual rate was  $-0.9 \pm 26.8$  cm/year (Figure 8b). In comparison, the average rates we calculated from published field measurements exhibit comparable magnitudes, with mean values of  $2.4 \pm 11.6$  cm/year for elevation change and  $3.9 \pm 3.8$  cm/year for accretion (Figure 8c; Twilley et al., 2022; CPRA, 2022). Rates of elevation change include RSET measurements (CPRA, 2022) averaging  $2.6 \pm 4.5$  cm/year and laser-level transect measurements (Bevington et al., 2017) averaging  $2.3 \pm 12.2$  cm/year. The residual rates derived from lidar-field comparisons fall within the range of rates derived from field measurements, indicating that the observed discrepancies between lidar and field elevations are consistent with expected rates of change in WLD. These results support the validity of lidar-derived elevations for quantifying decadal-scale elevation change.

We also evaluated whether elevation residuals vary systematically with vegetation structure, as suggested by previous studies in salt marsh environments (Schmid et al., 2011; Hladik and Alber, 2012; Medeiros et al., 2015), and therefore could be a systematic bias in the results due to inaccurate vegetation filtering. To test this hypothesis, each elevation residual acquired from field measurements between 2008 and 2021 (Figure 8a) was associated with a vegetation class. Although one-way ANOVA indicated statistically significant differences in elevation residuals among vegetation classes, the explained variance was negligible (1.4%). Instead, elevation residuals were more correlated with the time offset between lidar and field measurements (Pearson  $r = 0.55$ ) than with elevation itself (Pearson  $r = 0.22$ ), consistent with a rapidly evolving delta where temporal surface change is the dominant source of mismatch between lidar-derived and field-measured elevations, rather than vegetation-induced lidar bias. Because direct validation of lidar absolute elevations is confounded by rapid surface change, we evaluated lidar vertical accuracy using residual rates rather than residual magnitudes

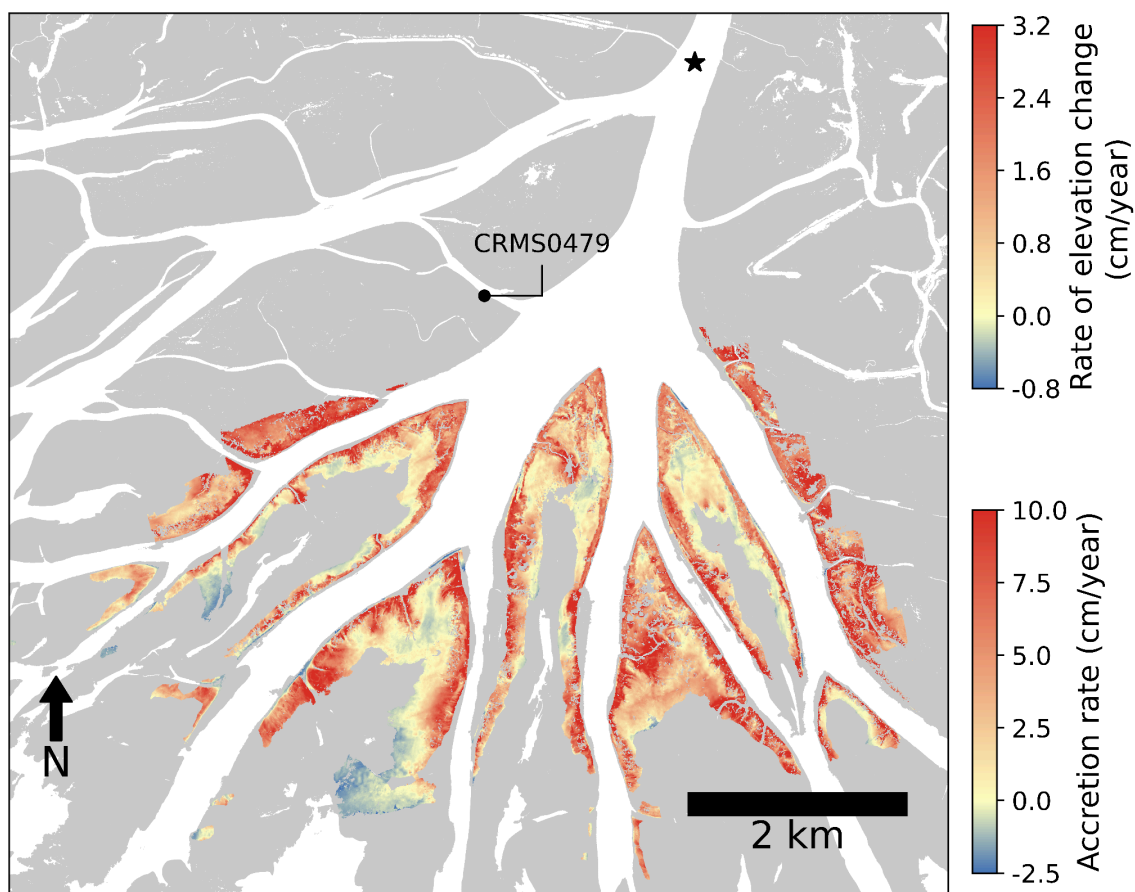


**Figure 8.** Comparison between elevation residuals from lidar-field measurements and the rates of change expected in WLD. (a) Location map of the absolute elevation datasets used (Bevington et al., 2017; Olliver & Edmonds, 2017; Rovai et al., 2022; Twilley & Rovai, 2022; Twilley et al., 2022), with each color representing different data sources, and each bracket showing their acquisition dates. The black star represents the WLD apex. (b) Histogram of the residual elevation change rate for the data to match the lidar, given the differences in time and elevation between the lidar and the field measurements. (c) Histogram of accretion and elevation change rate measurements in

WLD from different studies using different methods (RSET; CPRA, 2022, laser level; Bevington et al., 2017, and feldspar marker horizons; Twilley et al., 2022; CPRA, 2022).

#### *4.2. Accretion Rate and Trapping Efficiency of WLD*

The decadal accretion rate from 2009 to 2020 (Figure 9) had a mean value of 4.1 cm/year, a standard deviation of 3.7 cm/year, and a mean vertical uncertainty of 0.4 cm/year. These magnitudes are consistent with accretion rates we derived from field measurements in WLD ( $3.9 \pm 3.8$  cm/year; Figure 8c; Twilley et al., 2022; CPRA, 2022), and other measurements previously reported in WLD (Styles et al., 2017; Fontenot, 2022). The primary distinction in accretion rate is between island interiors and the levees of both primary and secondary channels, which is more pronounced than the trend between upstream and downstream regions (Figure 9). While most of WLD is net depositional, some areas experienced net erosion. These eroded areas occur along the upstream island margins, indicating that the islands are migrating downstream. Some distal regions within island interiors also lost elevation (Figure 9), as previously observed in satellite imagery of WLD (Smith et al., 2020).



**Figure 9.** The decadal rate of elevation change and accretion map for 2009-2020. The black star represents the WLD apex. Gray-shaded areas are regions sampled at least once by any lidar survey (Figure 2a). Note that negative values have different saturation levels for clarity.

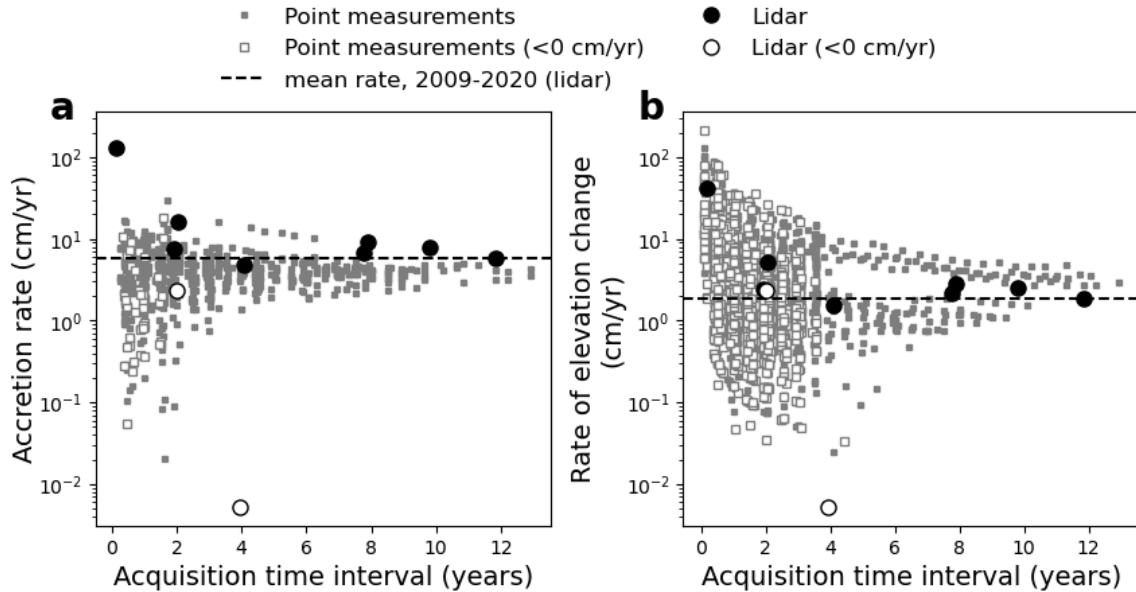
These accretion rates imply substantial sediment retention, motivating an estimate of trapping efficiency. Annually, WLD received 13.63 Mt/year from 2009 to 2013, 16.16 Mt/year from 2013 to 2020, and 15.29 Mt/year over the study period from 2009 to 2020. Using lidar-derived accretion maps from the same periods, the gross deposition rates were 289 kt/year, 256 kt/year, and 237 kt/year, respectively, and the gross erosion rates were 13 kt/year, 6 kt/year, and 1 kt/year. These measurements show that the region shared by the lidar surveys (3.58 km<sup>2</sup>) had a trapping efficiency of 2.12% during 2009-2013, higher than 1.58% during 2013-2020 and 1.55% over the entire study period. These estimates are biased low, however, because the lidar differencing only captured accretion over ~6.9% of the total subaerial island area.

If we assume that the average deposition rate that we measured is characteristic of the entire delta top (51.73 km<sup>2</sup>; Figure 2a), then WLD trapped 30.68%, 22.86%, and 22.39% during 2009-2013, 2013-2020, and 2009-2020, respectively (Table 2). The calculated trapping efficiency not only represents river mineral sediment retention, as we compared incoming riverine suspended sediments with the total accretion, which also integrates the cumulative deposits from local biogenic production and from sediments brought by marine events, e.g., storms. Nonetheless, the trapping magnitudes calculated are higher than the value ranges estimated before in WLD, 6.7-13.5% (Bevington et al., 2017). Their estimates are lower than ours, because we compensated for shallow subsidence; without this correction, our estimations of the trapping efficiency would be 7.2-9.8%.

**Table 2.** Breakdown of incoming riverine sediment flux, estimated deposited and eroded sediment mass, and the trapping efficiency in WLD during three intervals, 2009-2013, 2013-2020, and 2009-2020. The two rows of areas and trapping efficiencies correspond to the two approaches of calculations described in Section 3.6.

| Time interval | Time difference (year) | Riverine sediment flux (Mt/year) | Sediment load (kt/year) |         | Area (km <sup>2</sup> ) | Trapping efficiency (%) |
|---------------|------------------------|----------------------------------|-------------------------|---------|-------------------------|-------------------------|
|               |                        |                                  | Deposition              | Erosion |                         |                         |
| 2009-2013     | 4.08                   | 13.63                            | 289                     | -13     | 3.58                    | 2.12                    |
|               |                        |                                  |                         |         | 51.73                   | 30.68                   |
| 2013-2020     | 7.76                   | 16.16                            | 256                     | -6      | 3.58                    | 1.58                    |
|               |                        |                                  |                         |         | 51.73                   | 22.86                   |
| 2009-2020     | 11.84                  | 15.29                            | 237                     | -1      | 3.58                    | 1.55                    |
|               |                        |                                  |                         |         | 51.73                   | 22.39                   |

Accretion varies in time and depends on the timescale over which it is measured. The decadal mean rate of elevation change in WLD during the study period was  $1.2 \pm 1.3$  cm/year. In comparison, the delta has built at a mean rate of  $3.2 \pm 1.8$  cm/year since the channel was dredged in 1942 until the 2009 lidar acquisition, when the initial bathymetry was  $-2.1 \pm 0.66$  m. The comparison indicates that WLD experienced higher long-term mean rates of elevation gain during the past century than in the study period. In addition to differences in average rates across time intervals, we also observe that shorter measurement intervals tend to exhibit greater variability in rates of elevation change and accretion (Figure 10).



**Figure 10.** Compilation of rates of (a) accretion (feldspar horizon markers; Twilley et al., 2022; CPRA, 2022) and (b) elevation change (lidar, RSET; CPRA, 2022, and laser level; Bevington et al., 2017) of both lidar and point measurements against their acquisition time interval. Here, lidar-derived rates are limited to the overlap area of all lidar surveys (Figure 2a). Note the decrease in rate variability with increasing acquisition time intervals.

#### 4.3. Correlation Between Decadal Accretion Rates and Spatial Metrics

Accretion had distinct trends across the spatial metrics (Figure 11). Downstream of island apices, binned median accretion rates decreased from  $\sim 6$  cm/year at the island apex to  $\sim 3$ -4 cm/year between 1 and 4 km downstream, before fluctuating around  $\sim 0$  cm/year further downstream (Figure 11a). A similar downstream decline was observed relative to the WLD apex, but was more pronounced than the decline relative to individual island apices. However, despite these median trends, correlations between accretion rates and the distances from individual island apices and from the WLD apex were weak ( $r = -0.05$  and  $r = -0.14$ , respectively), reflecting high spatial scatter in accretion rates. Between 2 and 4 km from the WLD apex, median accretion rate decreased from  $\sim 12$  cm/year to 2 cm/year, and decreased further from  $\sim 4$ -5 cm/year at  $\sim 5$  km to negative accretion at distal regions beyond  $\sim 7$  km (Figure 11b).

Accretion also exhibited a moderate correlation with distance from island edge to island interior, consistent with the spatial patterns observed in the decadal accretion map (Figure 9). This trend produced the second-highest correlation with accretion rates

among the analyzed metrics ( $r=-0.37$ ) (Figure 11d). Binned median accretion rates decreased from  $\sim 6-7$  cm/year at  $\sim 60$  m from primary channels to near 0 cm/year within  $\sim 600$  m from island edges, before reaching  $-1$  to  $-2$  cm/year farther toward island interiors. Accretion rates were reduced immediately adjacent to island edges, partially due to bank erosion (Figure 9), decreasing median accretion to  $\sim 2.5$  cm/year (Figure 11d). In addition, secondary peaks in median accretion occurred between  $\sim 300$  and  $\sim 600$  m distance from island edges, where binned median accretion ranged from  $\sim 1$  to  $\sim 2.5$  cm/year. These local maxima suggest deposition in island interiors that are more connected to channel flow, for example, through secondary channels (Figure 9).

In the lateral direction, binned median accretion rates oscillated as a function of radial angle, extending from the western to eastern islands (Figure 11c). Accretion rates along local maxima ranged between  $\sim 5$  and  $\sim 9$  cm/year, whereas local minima ranged from  $\sim 0$  to  $\sim 2.5$  cm/year. Although these oscillations primarily reflect contrasts between levees and island interiors, median accretion rates demonstrated a weak eastward increase ( $r = 0.14$ ) (Figure 11c).

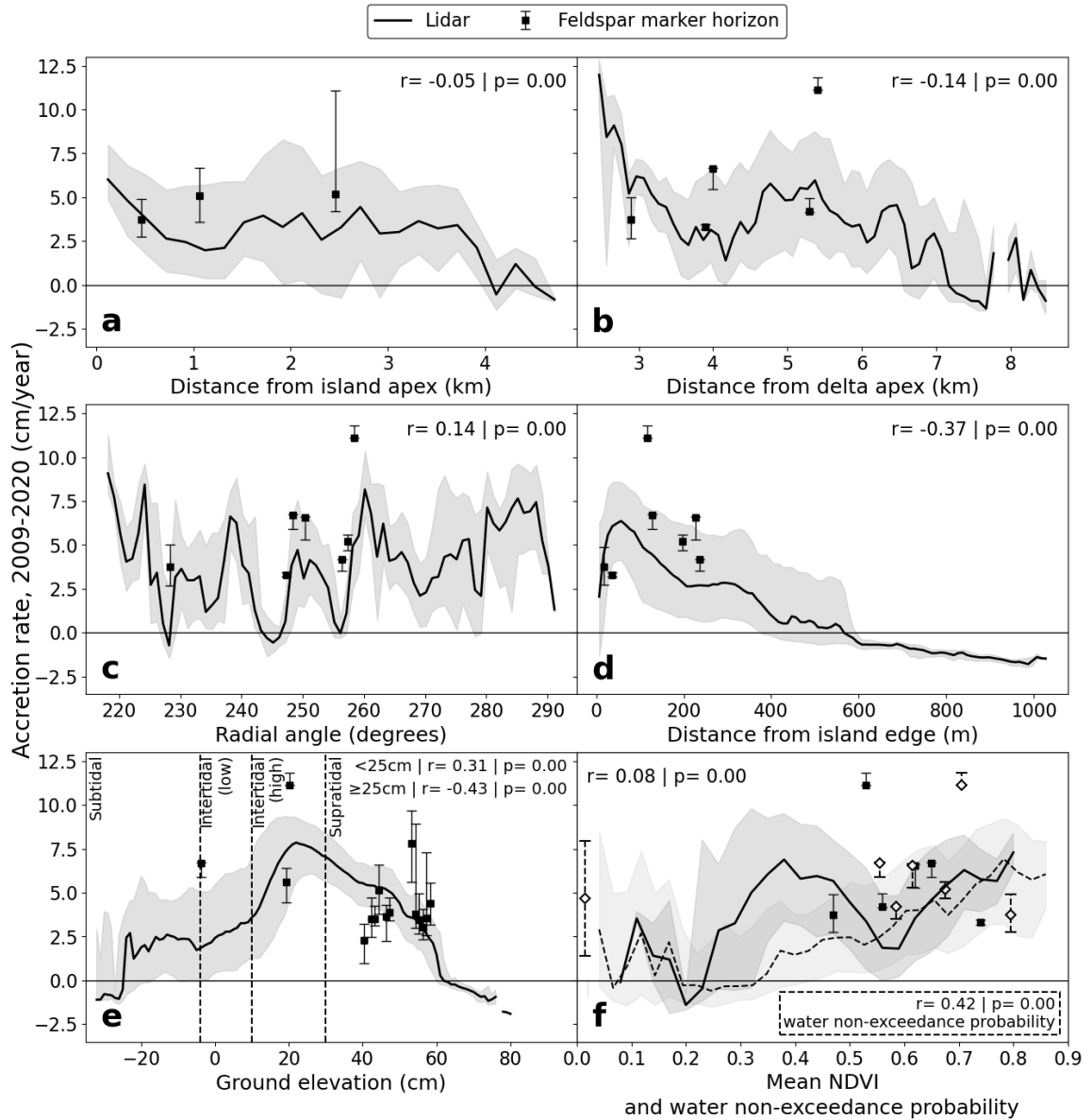
Accretion exhibited a nonlinear relationship with ground elevation, with trends converging near  $\sim 25$  cm in the ground elevation (Figure 11e). Median accretion increased from  $\sim -1$  cm/year at  $\sim 35$  cm elevation to  $\sim 8$  cm/year at  $\sim 20$  cm elevation. In contrast, elevations above  $\sim 20$  cm exhibited declining accretion rates through 2020, with regions above  $\sim 60$  cm experiencing net erosion. Despite this nonlinearity, accretion had one of the highest correlation coefficients with ground elevation ( $r = 0.31$  for elevations  $< 25$  cm,  $r = -0.43$  for elevations  $\geq 25$  cm). When classifying the 2009 ground elevation into hydrogeomorphic zones, mean accretion rates were  $5.37 \pm 2.51$  cm/year in supratidal regions,  $6.04 \pm 3.77$  cm/year in high intertidal regions,  $3.50 \pm 3.67$  cm/year in low intertidal regions, and  $2.72 \pm 2.26$  cm/year in subtidal regions (Figure 11e).

Mean NDVI exhibited only a weak positive relationship with accretion ( $r=0.08$ ) (Figure 11f). Regions with mean NDVI  $< 0.2$ , previously classified as unvegetated (Olliver & Edmonds, 2017; Finotello et al., 2024), showed median accretion rates fluctuating between approximately  $-1$  and  $5$  cm/year. Semi-vegetated regions (mean NDVI =  $0.2-0.4$ ; Finotello et al., 2024) exhibited higher median accretion rates, increasing to  $\sim 8$  cm/year, followed by a decline to  $\sim 2$  cm/year in densely vegetated regions with a mean NDVI near  $0.6$ . Median accretion rates increased again to  $\sim 8$  cm/year at mean NDVI values between  $0.6$  and  $0.8$  (Figure 11f). Accretion rates also differed among vegetation classes. Ordered by their typical elevation ranges (highest to lowest), mean accretion rates were: *Salix nigra* ( $5.85 \pm 3.18$  cm/year), *Polygonum punctatum* ( $6.84 \pm 3.29$  cm/year), *Colocasia esculenta* ( $6.57 \pm 2.99$  cm/year), Grasses ( $4.88 \pm 3.64$  cm/year), *Nelumbo lutea* ( $3.22 \pm 3.39$  cm/year), SAVs ( $2.44 \pm 2.97$  cm/year), Floating vegetation ( $1.34 \pm 2.96$  cm/year), and Water/Other ( $1.63 \pm 4.08$  cm/year). Overall, these class-averaged values suggest



that vegetation classes occupying higher elevations ( $\sim >40$  cm) were associated with higher mean accretion rates, although variability within each class was substantial.

In contrast to mean NDVI, water non-exceedance probability showed the strongest correlation with accretion rates among all analyzed metrics ( $r=0.42$ ). Although this correlation was moderate, binned median accretion displayed an overall positive trend with increasing water non-exceedance probability. However, regions with water non-exceedance probabilities between  $\sim 0.2$  and  $\sim 0.3$  experienced net erosion, whereas regions below  $\sim 0.2$  exhibited relatively higher accretion rates fluctuating between  $\sim 0$  and  $\sim 4$  cm/year (Figure 11f). While binned feldspar marker horizon measurements generally fall within the range of lidar-derived accretion rates, comparisons across all metrics highlight the limited spatial coverage of feldspar-based measurements (Figure 11).



**Figure 11.** Binned median accretion rate (cm/year) with shaded interquartile ranges, shown as a function of (a) distance from island apex, (b) distance from the WLD apex, (c) radial angle, (d) distance from the island edge, (e) ground elevation, and (f) mean NDVI and water non-exceedance probability. Binned median accretion rates derived from feldspar marker horizons (Twilley et al., 2022; CPRA, 2022) are shown as black squares with interquartile ranges (error bars) for the six metrics, and as white diamonds with dashed error bars for water non-exceedance probability. Pearson correlation coefficients ( $r$ ) and associated  $p$ -values ( $p$ ) were calculated using all values, rather than binned medians.

#### 4.4. Downstream Topographic Gradients and Elevation Populations

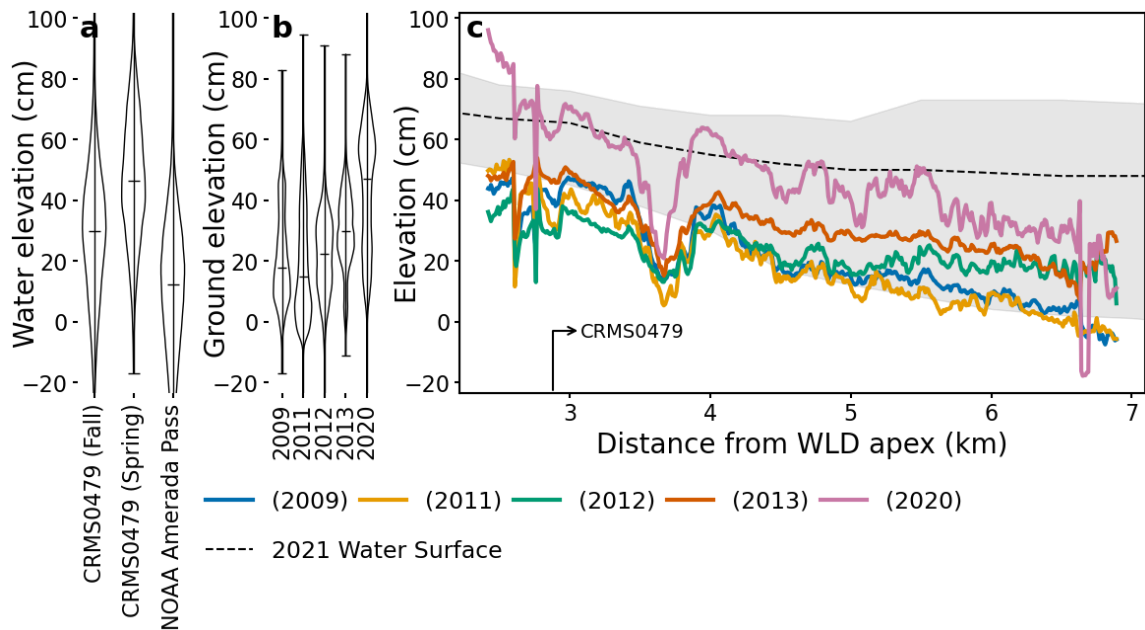
The downstream elevation profiles derived from the 2012 and 2013 lidar surveys were flatter than earlier surveys, with fitted gradients to median elevations of  $-3.8 \times 10^{-5}$  m/m and  $-6.2 \times 10^{-5}$  m/m, respectively. In contrast, the 2009 and 2011 profiles were steeper, with fitted gradients to median binned elevations near  $-1.0 \times 10^{-4}$  m/m (Figure 12c). This flattening is consistent with preferential elevation gain in downstream regions between 2011 and 2012. By 2020, approximately eight years after the 2013 survey, the downstream topographic profile returned to a slope similar to 2009 and 2011, with a fitted gradient to median elevations of  $-1.1 \times 10^{-4}$  m/m (Figure 12c), rather than being flatter than the 2013 profile, contrary to what was predicted by Wagner et al. (2017). This result suggests that the downstream gradient was reestablished by 2020, reflecting concentrated sediment accumulations in upstream regions. Because elevation profiles and distributions (Figure 12b-c) require spatial overlap across all lidar surveys, these analyses are limited to the overlap area sampled in every dataset (Figure 2a), which extends  $\sim 500$  m from island edges and  $\sim 7$  km downstream from the WLD apex. Nonetheless, the combined results indicate that low-elevation distal regions experienced greater elevation gain between 2009 and 2013, whereas upstream regions with higher elevations received relatively more sediment between 2013 and 2020 (Figure 12c).

To evaluate the association between inundation frequency and land building, we compared water surface elevations with lidar-derived ground elevations to assess where water levels were likely to exceed the land surface. Comparisons were performed using both binned downstream median profiles and elevation distributions. Binned median water surface elevations collected during spring 2021 are similar to ground elevations in 2020 across most of the study area (Figure 12c). Also, during spring, the minimum AirSWOT water surface elevations aligned closely with the 2009 and 2011 ground elevation profiles and exhibited a downstream gradient similar to the 2020 topography. Similarly, the steepest downstream AirSWOT water surface elevation gradient during high-flow regime in spring, reached a gradient of  $-9.3 \times 10^{-5}$  m/m when discharge was  $\sim 6060$  m<sup>3</sup>/s. In comparison, the steepest downstream AirSWOT water surface elevation gradient during fall was approximately  $-2.5 \times 10^{-5}$  m/m when discharge was  $\sim 2180$  m<sup>3</sup>/s. The maximum AirSWOT water surface elevations formed a relatively flat surface at  $\sim 70$ -80 cm and exceeded ground elevations across most of the delta, except within  $\sim 2$  km of the delta apex in 2020 (Figure 12c).

Consistent with these patterns, median lidar elevations from earlier surveys were generally lower than median water surface elevations measured at CRMS0479 during both seasons, whereas the 2020 lidar elevation distribution was shifted toward higher values. The median water surface elevation at CRMS0479 is  $\sim 45$  cm and can exceed 1 m during spring, whereas fall water levels typically range between 0 and 60 cm with a median near  $\sim 30$  cm (Figure 12a). This suggests that ground elevations, near CRMS0479,

that are higher than ~45 cm have approximately 50% less chance of inundation in spring. Still, the median water surface elevation is lower in downstream regions, as indicated by the water surface elevations in Amerada Pass. While water surface elevations at CRMS0479, ~3km from the apex, rarely drop below 0, water surface elevations at the Amerada Pass station, ~13.5 km SE from the WLD apex, can drop below -40 cm, with a median elevation at ~12 cm (Figure 12a).

Ground elevation distributions have previously been used to assess whether WLD is evolving toward multiple equilibrium elevations (Olliver & Edmonds, 2017; Smith et al., 2020). Here, we compare the distributions and modal elevations of ground elevations and measured water surface elevations to assess their alignment. Lidar elevation distributions can be grouped into three main groups, roughly separated at ~20 cm and ~40 cm (Figure 12b). The primary modes in 2009 and 2011 occur at ~10 cm and ~5 cm, respectively, whereas those in the 2012 and 2013 surveys occur at ~30 cm and ~25 cm. The 2020 survey exhibits the highest primary mode at ~55 cm (Figure 12b). Secondary modes are also present in each survey, occurring near ~45 cm in 2009, ~35 cm in 2011, ~15 cm in 2012, ~35 cm in 2013, and ~25 cm in 2020 (Figure 12b). Lidar elevation modes suggest that WLD has roughly three elevation platforms with local minima at ~20 cm and ~40 cm.



**Figure 12.** Downstream elevation gradients and elevation distributions in WLD. (a) Elevation histograms of water surface elevations measured at station CRMS0479 and at the Amerada Pass station (~13.5 km SE from the WLD apex). (b) Elevation histograms of

the five lidar surveys. (c) Median lidar ground elevations binned as a function of downstream distance from the WLD apex, using 10 m distance bins. For each bin, the median elevation is calculated from all lidar elevations within the corresponding distance interval. Linear fits and slopes were computed from the binned median elevations. These slopes and  $R^2$  values are:  $-1.0 \times 10^{-4}$  m/m and 0.84 (2009),  $-1.0 \times 10^{-4}$  m/m and 0.84 (2011),  $-3.8 \times 10^{-5}$  m/m and 0.53 (2012),  $-6.2 \times 10^{-5}$  m/m and 0.70 (2013),  $-1.1 \times 10^{-4}$  m/m and 0.68 (2020). The shaded zone is the maximum and minimum bounds of the Airborne Surface Water and Ocean Topography (AirSWOT) water surface elevations sampled in spring with a discharge range of  $\sim 5578$ - $6060$  m<sup>3</sup>/s. The displayed 2021 water surface profile is the binned median elevation.

## 5 Discussion

### 5.1. What determines land-building in a river delta?

The spatial trends of accretion and elevation change suggest that land building in WLD is strongly regulated by inundation depth and frequency. This dependence is reflected by the correlation between accretion and both ground elevation and water non-exceedance probability (Figure 11). The same relationship is evident in the alignment between the water surface elevations during spring 2021 and the lidar ground topography in 2020 (Figure 12c). In particular, accretion appears to be enhanced within an intermediate elevation range (high intertidal), suggesting a preferential window for sediment deposition and retention (Figure 11e). Although wetlands are generally expected to maintain elevations near mean sea level (Day et al., 2007), tidal oscillations in this microtidal system (35 cm range) may shift the elevation range most favorable for accretion toward higher elevations (Figure 11e).

The observed pattern along the elevation profile suggests that elevated areas ( $>40$  cm) predominantly received shallower and less frequent flows (Figure 1d; Figure 12a), which likely limited sediment supply to only fine fractions transported in the upper part of the water column. This interpretation is consistent with the negative trend of median decadal accretion rate with ground elevation within the supratidal zone (Figure 11e) and with the upward fining previously observed in WLD stratigraphy (Smith, 2014). As upstream areas aggrade beyond elevations that are frequently overtopped, they may become increasingly sediment-starved and begin to lose elevation (Bevington and Twilley, 2018). Instead, flow and sediment transport could bypass toward low-elevation regions and concentrate deposition downstream. Consistent with this interpretation, regions that had elevation  $>60$  cm in 2009 experienced net erosion or were depleted by 2020. Furthermore, bank erosion contributed to the negative rates of elevated upstream levees (Figure 9). In contrast, the low relief of island interiors and distal regions ( $>7$  km from the WLD apex) combined with low vegetation density and frequent deep

inundation flows may promote sediment resuspension and reworking by marine forces (Rosen and Xu, 2013; Hanegan & Georgiou, 2015; Whaling and Shaw, 2020). However, because distal island interiors are often submerged (Figure 2b), some of the apparent elevation loss may also reflect residual misclassification of water returns as ground elevations.

Although deposition was observed across WLD, proximity to sediment sources appears to be a primary control on land building. The correlation between accretion and the distance from island edges highlights the importance of sediment transport distance in shaping deposition patterns. In addition to the decay of transport capacity and the potential for sediment resuspension in island interiors, a decrease in grain size may enhance compaction farther from island edges (Smith, 2014; Beltrán-Burgos et al., 2023). Fine-grained, mud-rich deposits tend to undergo greater porosity loss, thereby reducing net elevation gain. In addition, proximity to river sediment supply may have allowed areas near the delta apex (<5 km from the WLD apex) to receive a larger fraction of the incoming sediment load and build higher topography (Figure 11b; Figure 12c). However, downstream distance demonstrated a weaker linear correlation with accretion than the distance from island edges. This contrast suggests that while the long-term emergence of WLD, or during 2009-2013 when 2011 major flood took place, is best expressed as a downstream gradient in accretion from the delta apex (Wagner et al., 2017; Bevington & Twilley, 2018), the spatial variability of accretion during the study period (2009-2020) is more strongly correlated with the distance from island edges.

The presence of vegetation appears to be associated with higher accretion in WLD, as regions with >0.2 mean NDVI generally exhibit higher accretion rates (Figure 12f). The large scatter in accretion, reflected by the weak linear correlation with mean NDVI, as well as the reduced accretion observed near mean NDVI ~0.6, suggests that the relationship between accretion and vegetation density is not monotonic. Mean NDVI reflects vegetation presence and long-term productivity (Shields et al., 2017; Bevington and Twilley, 2018), but it may not adequately capture vegetation structure or bed roughness. A strong nonlinear relationship has been reported previously between mean NDVI and accretion (Chenevert and Edmonds, 2024). Nonetheless, multiple vegetation metrics (mean NDVI, vegetation density, aboveground biomass, and vegetation classes) are correlated with, and potentially confounded by, other spatial gradients such as ground elevation and downstream distance from the WLD apex (Shields et al., 2017; Bevington and Twilley, 2018; Jensen et al., 2021), making it difficult to isolate vegetation effects. Still, the optimal production of aboveground and belowground biomass has been recorded in high-intertidal and supratidal (Jensen et al., 2022), which could have contributed to the accretion trend along ground elevation.

Although the correlation is weak, the variation in accretion with downstream distance from island apexes (Figure 11a) may reflect two mechanisms: enhanced sediment

deposition as flow bifurcates around the apex and loses transport capacity, or greater vegetation density near the apex that promotes sediment trapping. In the perpendicular (west-east) direction, the weak positive trend toward the east (Figure 11c) may reflect differences in channel geometry, as the East Pass is relatively deeper, shorter, and narrower, potentially channeling higher sediment concentrations (Wagner & Mohrig, 2019; Meselhe et al., 2021).

## *5.2. Why does the downstream gradient change in time?*

The temporal reversal of the deposition center between downstream to upstream regions (Figure 12c) could reflect several mechanisms. If accretion depends primarily on inundation depth and frequency, then the downstream topographic gradient would be expected to relax toward a single equilibrium elevation. However, although upstream areas were already elevated in 2013 and thus less frequently inundated, water surface elevations were not spatially uniform, particularly during spring. Higher upstream water surface elevations may have allowed high-relief levees to continue receiving overbank flow between 2013 and 2020, reaching elevations of ~80 cm and contradicting previous predictions of topographic flattening (Wagner et al., 2017). Still, mean ground elevations in 2020 were ~40 cm higher than in other lidar surveys (Figure 12b) and were also higher average water surface elevations (Figure 12a). Additionally, while regions with elevations exceeding 60 cm in 2009 were eroded, other upstream regions that should have been rarely flooded reached elevations exceeding 60 cm by 2020 (Figure 12c). This overshoot in elevation gain suggests that another mechanism is at play beyond regular annual floods.

Between 2013 and 2020, several hurricanes and major floods occurred. These extreme events raised the water surface above its normal levels (Figure 1d), allowing high-energy flows to deposit sediment upstream and thereby steepen the topographic gradient (Figure 12c). The large elevation gains are consistent with previous studies showing that major floods and hurricanes contribute disproportionately to sediment deposition in deltas (Bevington et al., 2017; Carle et al., 2015; Kenney et al., 2022). Preferential upstream deposition during intervals of hurricanes and storms has also been documented in previous studies in WLD (Whaling and Shaw, 2020; Smith et al., 2020). This interpretation is further supported by the large accretion and elevation gains following Hurricane Barry in 2019, which we calculated at the CRMS0479 station (see Methods 3.5). The relatively steep downstream gradient observed in earlier lidar ground elevations (2009 and 2011) may similarly reflect the influence of the major flood in 2008. In addition to overtopping elevated upstream levees, high-energy flows may carry a higher sand fraction. Due to its higher settling velocity, sand has a shorter transport reach, depositing closer to the source than finer fractions. Although no evidence for downstream grain-size decay has been documented in WLD (DuMars, 2002), recent

extreme events may produce a downstream grain-size gradient in addition to the elevation gradient.

The consistent deposition downstream, between ~4 and 7 km from the WLD apex, throughout the study period (Figure 12c) could reflect either continuous deposition processes or episodic deposition during extreme events. Although farther from the sediment source, deposition in downstream regions may be due to their accessible intertidal elevations. Alternatively, the downstream deposition could have been driven primarily by the major flood in May-June 2011 (Figure 1d; Carle et al., 2015). As such, the period between 2011 and 2012 may reflect deposition patterns distinct from those associated with other extreme events (Carle et al., 2015). Although the 2011 flood reached higher magnitudes, both major flood and hurricane occurrences raised the water levels and river discharges to high magnitudes (Figure 1d). Beyond these temporal associations, the available data do not allow us to distinguish between the relative effects of hurricanes, storms, and major floods.

### *5.3. Topographic steady state in WLD*

Accretion measurements taken at intervals shorter than ~2-4 years may capture rapid changes driven by individual high-impact events (Figure 10). In contrast, longer intervals may reflect the long-term mean accretion rates (Sadler, 1981). Notably, a four-year timescale has been observed to effectively smooth interannual variability in the total land area of WLD (Olliver & Edmonds, 2017). Moreover, we found that the recurrence timescale of major floods was ~2-3 years (Figure 1d), which is shorter than the separation time observed in the temporal decay of accretion variability (Figure 10). This timescale is also shorter than the 11-12 year recurrence interval previously estimated from historical records (Bevington et al., 2017; Whaling and Shaw, 2020), highlighting the increased importance of extreme events over recent decades. The separation timescale may therefore represent the time required for the delta to reach a quasi-steady-state condition.

Topographic steady state is commonly evaluated based on the elevation structure of the delta. The association between accretion rate and elevation (Figure 11e) suggests an equilibrium elevation at ~60 cm across the delta; as land is built toward this elevation, accretion decreases as inundation frequency decreases. A similar equilibrium elevation in WLD was previously proposed at 56cm (Wagner et al., 2017). Wagner et al. (2017) acknowledged that even if extreme events caused an “overshoot” above the equilibrium elevation, the additional relief would erode over time. However, their analysis was limited to a relatively short time interval (2009 and 2013), during which the 2011 major flood was associated primarily with downstream deposition. Our results indicate that upstream and downstream portions of WLD had not converged to a unified elevation by 2020 (Figure 12). Contrary to predictions that downstream accretion would flatten the



downstream profile, upstream accretion has steepened the topographic gradient, exceeding the proposed equilibrium elevation of 56cm. If the upstream elevation gain is persistent rather than transient, achieving a steady state condition with a single equilibrium elevation across WLD appears unlikely. Instead, the bimodal distributions of ground elevations may suggest spatially distinct equilibrium elevations. This is reflected by elevation modes punctuated at ~20 cm and ~40 cm (Figure 12), consistent with vegetation zonation in WLD with a local minimum at ~40 cm.

Nonetheless, in a river-dominated delta where sediment supply exerts a dominant control, topographic steady state is unlikely to be determined solely by vegetation. The downstream-steepening topographic gradient and the alignment between water surface and ground elevations may reflect a tendency for the delta to fluctuate around an equilibrium gradient. This equilibrium gradient may arise from differences in inundation thresholds between upstream and downstream regions. Notably, the persistent contrast in elevation and accretion between levees and island interiors could indicate the presence of an equilibrium negative gradient toward island interiors. The decay of sediment supply, as overbank flows lose transport capacity, would promote greater deposition at island edges where levees form and aggrade, whereas island interiors may receive sediments only sufficient to remain within a narrower elevation range. This gradient in accretion has been observed previously in WLD, but was considered abrupt and transient rather than gradual and stable (Olliver and Edmonds, 2017; Wagner et al., 2017).

#### *5.4. Combating submersion by sea level rise*

Despite strong spatial variability, the rates of land building provide a first-order quantity for evaluating whether the delta keeps pace with sea level rise. The average decadal accretion rate of  $4.1 \pm 3.7$  cm/year in WLD exceeds an estimated relative sea level rise rate in South Louisiana of  $1.2 \pm 0.83$  cm/year, which incorporates sea level rise and both deep and shallow subsidence (Jankowski et al., 2017). In comparison, the semi-centennial rate of elevation gain from 1942 to 2009 is nearly triple the recent decadal rate, suggesting that land building may have been more rapid at early stages of WLD development, potentially during the subaqueous growth stage (Olliver and Edmonds, 2017), whereas more recent rates may reflect reduced sediment supply (Blum and Roberts, 2009; Rosen and Xu, 2013). Subaqueous land building in WLD may not have begun until 1952 (Wellner et al., 2005); therefore, averaging over the 1942-2009 interval likely underestimates the long-term accretion rate by including years prior to delta initiation. Nevertheless, the observed accretion rates provide no clear evidence of delta-wide degradation over the study period, consistent with the high survival potential of deltas of similar size (Giosan et al., 2014). Mean lidar-derived accretion rates are broadly consistent with field-based estimates, but pronounced variability of accretion in space (Figure 9; Figure 11) and time (Figure 10) highlights the limitations of spatially

biased averages and underscores the value of spatially continuous lidar-based measurements.

Our results identify elevation and distance thresholds that control vulnerability to submersion in WLD. Distal regions located ~7 km from the delta apex at elevations below -10 cm, as well as island interiors more than 600 m from island edges, were most vulnerable. In addition, regions above 60 cm in elevation also experienced erosion, possibly due to reduced inundation frequency. These patterns imply that distance and elevation thresholds for land survival may shift upward and move closer to sediment sources as sea level rises. However, extreme events (e.g., major floods and hurricanes) may exceed these thresholds. The 2011 flood not only modified the downstream topographic gradient (Figure 12) but also enhanced the trapping efficiency of the delta (Table 2), a quantity controlled by local hydrodynamics and vegetation (Fagherazzi et al., 2015; Beltrán-Burgos et al., 2023). Our results suggest that extreme events, more than vegetation, may play an important role in enhancing sediment trapping (Table 2; Bevington et al., 2017). However, reduced sediment fluxes due to dams and engineered levees may limit this advantage (Rosen & Xu, 2013), and rising sea levels may limit vegetation expansion and resilience (Carle et al., 2015; Bevington et al., 2022). Overall, our findings suggest that even as levees keep pace with sea level rise, island interiors may remain vulnerable to submersion because sediment deposition decays exponentially with distance from levees.

### *5.5. Lidar as a tool for measuring accretion*

A decade of repeat lidar surveys enabled the measurement of accretion rates in the rapidly evolving Wax Lake Delta (WLD) at high spatial resolution and over broad spatial extents. By mapping ground elevation and elevation change, lidar provided substantially greater spatial detail and coverage than satellite imagery or field measurements alone (Figure 8a; Figure 11).

Because lidar differencing captures elevation change rather than accretion, we incorporated a correction derived from field measurements to account for shallow subsidence (Figure 6). This approach avoids omitting shallow subsidence entirely and provides an alternative to applying a spatially uniform shallow subsidence rate. Although the derived relationship between accretion and elevation change (Equation 4) may vary spatially across the delta due to local sediment properties and compaction processes, the CRMS0479 record provides a reasonable first-order estimate constrained by more than a decade of repeated field measurements. Moreover, the consistency between accretion rates derived from lidar differencing and those obtained from ground measurements supports the applicability of this approach at the delta scale.

The combination of careful lidar processing and the rapid growth in WLD, which exceeds typical vertical lidar uncertainties, increases confidence in the decadal accretion patterns reported here. Field measurements generally fall within the interquartile ranges of binned lidar-derived accretion rates and follow similar trends, but lidar provides broader spatial coverage across all analyzed metrics. These results support the use of lidar as a powerful tool for monitoring and quantifying accretion patterns in deltaic environments.

## 6 Conclusion

Elevation is a key parameter in the ecology and geomorphology of deltas. Lidar differencing shows that the subaerial lands of WLD grew vertically between 2009 and 2020, at a mean rate of  $1.24 \pm 1.3$  cm/year. Their accretion rate of  $4.1 \pm 3.7$  cm/year surpassed the estimated rates of relative sea level rise in South Louisiana,  $1.2 \pm 0.83$  cm/year, yielding trapping efficiencies of ~22-31%. Accretion varied significantly with distinct trends in both space (Figure 9; Figure 11) and time (Figure 10), highlighting the limitations of using a single representative accretion rate or spatially restricted field measurements. Regions close to sediment sources, including the delta apex, island apices, and channel edges, with high-intertidal elevation levels accessible to inundation, experienced the highest accretion rates (~7 cm/year), compared to 2.5 cm/year in distal, low-relief regions. Periods with multiple hurricanes and major floods (2013-2020) favored deposition in upstream reaches, whereas enhanced deposition might be associated with the 2011 major flood. Our results suggest that the gradient of the river water surface, which governs sediment supply during floods, drives spatial patterns in inundation frequency and deposition, promoting land building in low-elevation downstream areas and limiting sediment supply to higher upstream regions. Locally, accretion variability, mainly induced by vegetation and proximity to island edges, may cause the delta topography to decouple from the water surface elevation. The lidar-based analyses in this study provide a robust framework for quantifying accretion patterns informing future process-based and restoration studies of river deltas.

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### Supporting Information

The absolute elevation measurements were measured with a Trimble R12 GPS unit in March and August 2021 as part of the NASA Delta-X project, with horizontal and vertical uncertainties of 8 mm and 15 mm, respectively. The points were measured using the rover unit mounted on a 2-m survey rod. The data processing used corrections from the Trimble R12 base station and nearby GNSS reference stations.

**Table S1.** Elevation data points (NAVD88 m – GEOID18) collected in Mike Island in WLD in 2021.

| id | easting    | northing   | elevation | time          | description      |
|----|------------|------------|-----------|---------------|------------------|
| 1  | 650732.253 | 3265558.74 | 0.405     | 3/26/21 12:10 | Mike Island West |
| 2  | 650732.328 | 3265556.64 | -0.007    | 3/26/21 12:24 | Mike Island West |
| 3  | 650732.473 | 3265558.01 | 0.347     | 3/26/21 12:25 | Mike Island West |
| 4  | 650734.836 | 3265555.05 | 1.287     | 3/26/21 12:27 | Mike Island West |
| 5  | 650736.341 | 3265552.22 | 0.591     | 3/26/21 12:28 | Mike Island West |
| 6  | 650742.928 | 3265548.32 | 0.853     | 3/26/21 12:30 | Mike Island West |
| 7  | 650748.358 | 3265544.75 | 0.428     | 3/26/21 12:31 |                  |
| 8  | 650754.197 | 3265540.49 | 0.393     | 3/26/21 12:32 |                  |
| 9  | 650754.197 | 3265540.49 | 0.393     | 3/26/21 12:32 |                  |
| 10 | 650759.329 | 3265533.9  | 0.422     | 3/26/21 12:33 |                  |
| 11 | 650765.975 | 3265527.36 | 0.404     | 3/26/21 12:34 |                  |
| 12 | 650773.478 | 3265518.92 | 0.346     | 3/26/21 12:35 |                  |
| 13 | 650778.73  | 3265516.03 | 0.24      | 3/26/21 12:37 |                  |

|    |            |            |        |               |                    |
|----|------------|------------|--------|---------------|--------------------|
| 14 | 650780.122 | 3265513.95 | -0.014 | 3/26/21 12:39 | bottom under water |
| 15 | 650780.127 | 3265513.95 | -0.039 | 3/26/21 12:39 | bottom under water |
| 16 | 650790.208 | 3265506.75 | -0.127 | 3/26/21 12:41 | bottom under water |
| 17 | 650790.59  | 3265507.25 | 0.261  | 3/26/21 12:43 | water surface      |
| 18 | 657509.108 | 3286645.84 | 1.496  | 3/27/21 8:24  |                    |
| 19 | 657509.329 | 3286645.7  | 1.419  | 3/29/21 6:48  |                    |
| 20 | 651209.814 | 3263619.27 | -0.27  | 3/29/21 11:39 | Mike Island East   |
| 21 | 651205.108 | 3263619.09 | -0.088 | 3/29/21 11:43 | Mike Island East   |
| 22 | 651201.223 | 3263620.99 | -0.039 | 3/29/21 11:45 | Mike Island East   |
| 23 | 651194.68  | 3263622.58 | 0.2    | 3/29/21 11:47 | Mike Island East   |
| 24 | 651191.504 | 3263622.62 | 0.268  | 3/29/21 11:48 | Mike Island East   |
| 25 | 651182.496 | 3263623.27 | 0.259  | 3/29/21 11:49 | Mike Island East   |
| 26 | 651179.013 | 3263622.47 | 0.216  | 3/29/21 11:50 | Mike Island East   |
| 27 | 651173.008 | 3263622.05 | 0.246  | 3/29/21 11:52 | Mike Island East   |
| 28 | 651164.233 | 3263618.51 | 0.302  | 3/29/21 11:54 | Mike Island East   |
| 29 | 651150.884 | 3263618.84 | 0.207  | 3/29/21 11:56 | Mike Island East   |
| 30 | 651141.858 | 3263618.18 | 0.215  | 3/29/21 11:57 | Mike Island East   |
| 31 | 651134.253 | 3263618.98 | 0.141  | 3/29/21 11:58 | Mike Island East   |
| 32 | 651134.253 | 3263618.98 | 0.141  | 3/29/21 11:58 | Mike Island East   |
| 33 | 651121.384 | 3263622.89 | 0.051  | 3/29/21 12:00 | Mike Island East   |
| 34 | 651108.702 | 3263626.34 | 0.018  | 3/29/21 12:02 | Mike Island East   |
| 35 | 651094.117 | 3263630.64 | 0.017  | 3/29/21 12:03 | Mike Island East   |
| 36 | 651055.306 | 3263641.8  | -0.073 | 3/29/21 12:05 | Mike Island East   |
| 37 | 651012.951 | 3263654.25 | -0.182 | 3/29/21 12:08 | Mike Island East   |
| 38 | 650974.591 | 3263663.54 | -0.413 | 3/29/21 12:12 | Mike Island East   |
| 39 | 651307.275 | 3263279.38 | 0.163  | 3/29/21 13:34 |                    |
| 40 | 651318.59  | 3262575    | -0.299 | 3/29/21 14:53 | Mike Island East   |
| 41 | 651312.791 | 3262575.2  | -0.088 | 3/29/21 14:54 | Mike Island East   |
| 42 | 651308.956 | 3262575.53 | -0.017 | 3/29/21 14:56 | Mike Island East   |

|    |            |            |        |               |                  |
|----|------------|------------|--------|---------------|------------------|
| 43 | 651289.523 | 3262583.35 | 0.083  | 3/29/21 14:57 | Mike Island East |
| 44 | 651271.828 | 3262589.41 | 0.07   | 3/29/21 14:58 | Mike Island East |
| 45 | 651271.828 | 3262589.41 | 0.07   | 3/29/21 14:59 | Mike Island East |
| 46 | 651252.247 | 3262593.85 | 0.047  | 3/29/21 15:00 | Mike Island East |
| 47 | 651234.745 | 3262597.01 | -0.093 | 3/29/21 15:01 | Mike Island East |
| 48 | 651219.681 | 3262599.73 | -0.166 | 3/29/21 15:03 | Mike Island East |
| 49 | 651219.587 | 3262599.73 | -0.037 | 3/29/21 15:04 |                  |
| 50 | 651314.666 | 3262576.53 | 0.446  | 3/29/21 15:14 |                  |
| 51 | 711753.987 | 3228958.89 | 0.382  | 8/17/21 10:57 |                  |
| 52 | 711739.473 | 3228957.94 | 0.186  | 8/17/21 14:19 |                  |
| 53 | 711566.841 | 3228945.42 | -0.287 | 8/19/21 14:46 |                  |
| 54 | 651217.608 | 3263657.76 | -0.576 | 8/20/21 15:15 |                  |
| 55 | 650713.021 | 3265527.29 | -0.184 | 8/20/21 15:32 |                  |
| 56 | 711739.21  | 3228957.59 | -0.188 | 8/23/21 12:35 |                  |
| 57 | 651156.069 | 3265421.46 | -0.534 | 8/24/21 8:11  |                  |
| 58 | 650968.363 | 3263704.92 | -0.232 | 8/24/21 8:24  |                  |
| 59 | 651187.424 | 3263596.21 | 0.28   | 8/24/21 11:00 |                  |
| 60 | 650985.683 | 3261459.11 | 0.012  | 8/24/21 12:01 |                  |
| 61 | 651249.502 | 3262227.13 | -0.052 | 8/24/21 13:04 |                  |
| 62 | 651179.644 | 3263219.11 | 0.484  | 8/24/21 13:56 |                  |
| 63 | 651179.679 | 3263219.08 | 0.374  | 8/24/21 14:01 |                  |

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## CHAPTER 3: SECONDARY CHANNELS AS SEDIMENT DELIVERY CONDUITS TO DELTAIC ISLANDS

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### Abstract

The survival of river deltas hinges on the ability of deltaic islands to retain sediment. Progressive settling of sediment advected into islands yields an exponential decay of accretion rates away from island edges, meaning that island interiors should drown relative to island edges. These predictions, however, are at odds with stable island topography in growing deltas. Here, we used repeat lidar surveys to show that secondary channels—conduits that connect main deltaic channels to island interiors—transport at least 15% of the sediment needed to sustain islands in Wax Lake Delta (WLD), Louisiana, USA. Secondary channels terminate in depositional lobes that accrete at rapid rates that match island levees ( $\sim 10.5$  cm/year) and cover 14.3% of island interiors. Decadal cycles of secondary channel formation, rapid lobe building, and backfilling create compensational stacking deposits that are critical to sustaining deltaic wetlands.

### 1 Introduction

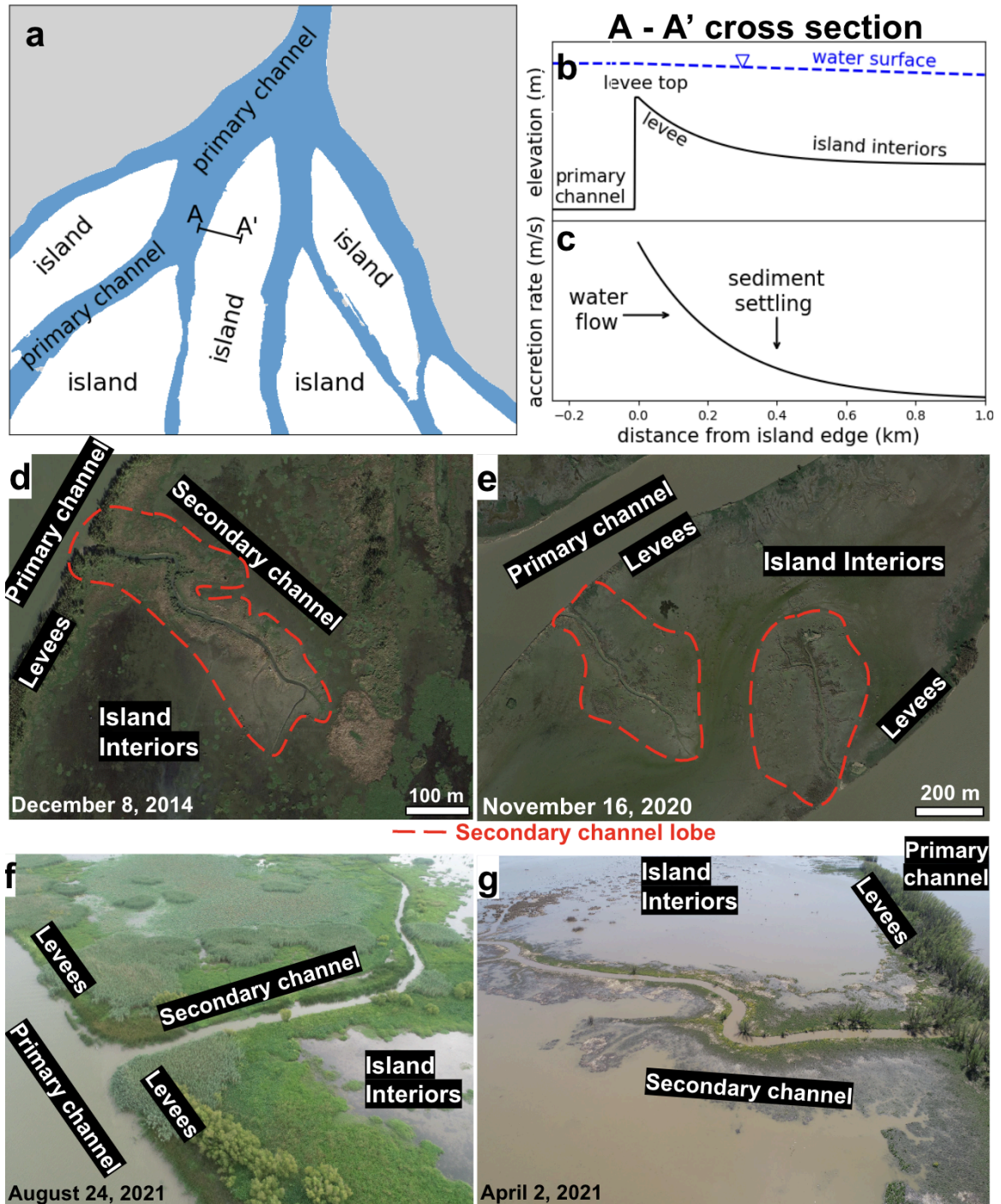
Deltas are increasingly unable to keep pace with rising sea levels due to declining sediment supply, driven by upstream dams and levees, and high rates of subsidence in rapidly compacting, muddy deposits (Blum & Roberts, 2009; Nienhuis et al., 2020). The persistence of deltaic land, therefore, hinges on the ability to retain sediment at rates comparable to relative sea-level rise (Kim et al., 2009; Twilley et al., 2019). Deltas are composed of a network of persistent channels that bifurcate around islands (Figure 1a). Within a deltaic island, sediment advection-settling models predict an exponential decay of accretion rates away from island edges (Figure 1b-c), meaning that island interiors are predicted to submerge relative to island edges (Day, 2008; Edmonds et al., 2011; Salter and Lamb, 2022). These predictions, however, are at odds with seemingly stable island topography in growing deltas (Edmonds et al., 2011), indicating that an additional mechanism is needed to deliver sediment to island interiors.

Major restoration efforts are underway to save sinking coastal deltas, but we still do not fully understand the mechanisms responsible for island sedimentation (Kim et al., 2009;

Paola et al., 2011). One of the main mechanisms discussed for coastal land building is vegetation-mediated accretion. Although vegetation may slow the flow through friction and enhance the magnitude of sedimentation rates locally by binding sediment or limiting re-entrainment (Mudd et al., 2010; Fagherazzi et al., 2012), these processes only act to shorten the characteristic distance into the island interior over which the exponential decay in sedimentation occurs in deltaic islands (Nardin & Edmonds, 2014; Hiatt & Passalacqua, 2015). So, despite being appropriate for some restoration goals, vegetation might actually exacerbate sediment starvation of island interiors relative to island edges (Nardin and Edmonds, 2014; Salter and Lamb, 2022). Vegetation can also contribute directly to accretion via below-ground organic matter (Morris et al., 2002), but organic matter is a small component of accretion rates in fluvial-dominated deltas of concern here (Shields et al., 2017; Bevington & Twilley, 2018).

Another main mechanism proposed to drive island accretion is through sediment delivery by secondary channels (Giosan et al., 2013; Hiatt & Passalacqua, 2015; Passalacqua, 2017). Secondary channels are channels, much smaller than the primary deltaic channels, that cut across island levees and terminate as depositional lobes in island interiors (Figure 1d-g). Because secondary channels can sustain elevated boundary shear stresses relative to unchannelized flow, deposited sediment can be re-entrained along the transport path, bypassing island edges and contributing more substantially to island interior accretion (Rowland et al., 2009; Salter and Lamb, 2022). This hypothesis, however, has been difficult to test. While point-based field observations confirm that accretion rates near secondary channels can be high (Shen et al., 2015; Esposito et al., 2017), these data are spatially limited, and the attribution of secondary channel accretion at the scale of a delta is unclear. Restoration efforts are engineering diversions that mimic secondary channels (Coastal Protection and Restoration Authority, 2023; Esposito et al., 2017), but we still do not fully understand whether natural secondary channels contribute substantially to island accretion in deltas.

Here, we tackle this knowledge gap by differencing a series of airborne lidar surveys (2009, 2012, and 2020) in the Wax Lake Delta (WLD), a rapidly evolving, river-dominated delta that is part of the Mississippi Delta complex, Louisiana, USA. We map the lobate landforms of secondary channel deposits and measure their accretion rates relative to those along levees and in unchannelized island interiors. These data reveal that secondary channels terminate in large depositional lobes that cover a substantial portion of the delta-top area and have exceptionally large accretion rates. Our results show that sediment transport through secondary channels is the dominant mechanism, relative to overbank deposition, sustaining deltaic island interiors, with broad implications for delta restoration and management.



**Figure 1.** (a) Example deltaic islands bifurcated by persistent primary channels. (b) cross section A-A' showing the elevation profile of levees and island interiors, and (c) the decay of accretion rate from island edges to interiors as predicted by the advection-settling model. (d-g) Plan-view images of secondary channels connecting primary channels to island interiors at Wax Lake Delta, USA. Panels (d and e) are Google

Earth satellite imagery, while panels (f and g) are drone images. Panels (d-e) illustrate secondary channel depositional lobes identified as lobate landforms. The locations of the secondary channels are annotated in Figure 2a as (1) for the channel in panels (d) and (g), (2 and 3) for the channel lobes in panel (e), and (36) for the channel in panel (f).

## 2 Study Area

The Wax Lake Delta (WLD) is a rapidly evolving river-dominated delta in the Mississippi Delta complex, South Louisiana. WLD consists of teardrop-shaped islands separated by primary channels (Figure 1a) that are more than 100 m wide and 1-4 m deep (Hiatt and Passalacqua, 2015; Shaw et al., 2016). The islands have higher topography and denser vegetation upstream (Bevington & Twilley, 2018), with average accretion rates of  $\sim 4.17 \pm 2.28$  cm/year (CPRA, 2022). Island morphology is narrower upstream and wider toward the gulf, while the topography is steeper from island edges to island interiors closer to island apices and flatter towards the bay (Bevington & Twilley, 2018).

Secondary channels of varying sizes incise these islands at approximately orthogonal angles to the primary channels (Figure 1d-g). These secondary channels have been observed in both subaerial and subaqueous regions of WLD, with channel widths up to  $\sim 45$  m (Hiatt and Passalacqua, 2015). The flow in smaller secondary channels can be modulated by the bidirectional tidal action (Hiatt and Passalacqua, 2015). Two decades of satellite imagery, although at relatively low resolution (30 m), indicate that subaerial emergence in WLD is fastest along secondary channels (Olliver & Edmonds, 2017; Smith et al., 2020), with rates of elevation gain reaching  $>4$ -5 cm/year along these channels (Smith et al., 2020). Because it surveys large subaerial lands with high resolution, lidar has the potential to measure and map elevation gains by secondary channels across the deltaic islands of WLD.

## 3 Methods

### 3.1. Lidar processing

We use lidar surveys acquired in 2009, 2012, and 2020 to quantify elevation, elevation change, and accretion at secondary channel lobes in WLD. All lidar datasets (Alqattan & Lamb, 2026; Supporting Information Text S1) were converted to a common reference frame (NAD83 2011, NAVD88-GEOID18) and vertically co-registered using six stable benchmark structures across the delta to remove delta-wide elevation offsets (Supporting Information Text S2). Because water returns had already been classified in the 2012 and 2020 datasets but not in the 2009 dataset, the 2009 survey required an additional classification workflow to separate water from land returns using lidar-derived features (Supporting Information Text S3). For each survey, low-lying

vegetation was then removed using a ground-filtering workflow designed to preserve geomorphic surfaces such as levees (Supporting Information Text S4).

After isolating ground returns, we calculated pointwise elevation differences using the Multiscale Model-to-Model Cloud Comparison (M3C2; Lague et al., 2013) tool in CloudCompare and gridded the resulting elevation changes to 2 m resolution (Supporting Information Text S5). To estimate accretion rather than net ground elevation change, we corrected the lidar-derived elevation changes for shallow subsidence using a linear relationship between field-measured accretion thickness and the offset between accretion and elevation change (i.e., shallow subsidence) (Supporting Information Text S6). This relationship suggests that shallow subsidence accounted for approximately 68% of the overburden accretion, and we applied this correction across WLD to convert elevation change to accretion.

### *3.2. Mapping secondary channels and their lobes*

Our objective was to map depositional lobes associated with secondary channels to estimate the fraction of island accretion expressed as discrete lobe deposits and to document channel evolution over time. Secondary channels were identified from the 2009, 2012, and 2020 lidar elevation maps as elongate topographic depressions extending from the levees of primary channels into island interiors. Where lidar coverage was incomplete, channel centerlines were traced in Google Earth imagery acquired between 2009 and 2020 along linear-to-sinuuous features that were visually distinct from the surrounding floodplain. For each channel, a single centerline was manually digitized following the longest observed channel extent across all available datasets.

Channel lobes were mapped along secondary channels where identifiable lobate landforms were present (Figure 1d-e). A lobe was defined as an elongate or fan-shaped depositional surface that slopes away from the secondary channel toward adjacent non-channelized island interiors, with margins recognizable in lidar from a distinct break in slope, curvature, or contour pattern relative to adjacent floodplain surfaces (Figure S1). Lobe boundaries were manually delineated along the outer edge of this morphologically distinct surface. Channels lacking a clearly mappable lobe, or channels outside the area covered by the 2012 or 2020 lidar surveys, were excluded from the lobe analysis. Because this procedure captures only deposits expressed as morphologically distinct lobes, it likely provides a minimum estimate of deposition associated with secondary channels; additional sediment delivered through these channels may be deposited as a thin drape across the floodplain and would not be included in the mapped lobe area.

### *3.3. Estimation of accretion averages and patterns in secondary channel lobes and in unchannelized regions*

Two of the primary objectives of this study were to gauge the extent of accretion introduced into deltaic islands by secondary channels and to determine whether it accumulates at a rate sufficient to match levee aggradation. Since the lobate landforms around secondary channels are directly linked to secondary-channel deposition, we divided the lidar regions into unchannelized and secondary-channel-lobe regions. The generated pointwise and gridded maps of accretion, as explained in Section 3.1, were labeled as part of secondary channels if they fell within the manually drawn secondary channel lobe geometries. The mean accretion rate of secondary channel lobes was calculated from all the accretion map cells (2012-2020) identified within secondary channel lobes (Figure 2a-b). In addition to the delta-scale average accretion rates within secondary channel lobes, we investigated the 2012-2020 accretion patterns as a function of two parameters: ground elevation (i.e., the 2012 elevation) and distance from island edges (Figure 3). Here, binned median accretion rates were calculated from all accretion rate map cells, once for all map cells within secondary channel lobes and once for all accretion rate map cells outside of these lobes, as a function of the two parameters. The distances from the island edges of all observation points and map cells of elevation and accretion were calculated from manually drawn island polygons (Figure S2).

To examine whether rates within secondary channel lobes keep pace with levee aggradation, we delineated accretion rates along levees in unchannelized regions. First, regions outside of secondary channel lobes were considered unchannelized. Next, we extracted a median characteristic distance that defines the levee extent ( $L_{t,levee}$ ), starting from the island edges (Supporting Information Text S7; Figure S3; Figure S4). This distance was calculated as the  $e$ -folding distance inverted from accretion rates versus distances from island edges along several transects perpendicular to unchannelized levees. Using all map cells, values within the median levee extent ( $L_{t,levee}$ ), starting from island edges, were labeled as levees, and, as with secondary channel lobes, their mean accretion rates were calculated. We also performed a sensitivity test to assess the effect of varying the characteristic levee extent ( $L_{t,levee}$ ) on the calculated mean accretion rates of levees (Figure S5).

### *3.4. Geometry and elevation profiles of secondary channels*

Besides the delta-scale accretion rates of secondary channels, their temporal and spatial evolution is poorly constrained. The rapid activity of the secondary channel through lobe formation and progradation between 2009 and 2020 in WLD presented an opportunity to fill some of these gaps. To investigate the evolution of each secondary channel, we



extracted the radially binned median elevation profiles at 2009, 2012, and 2020 as a function of distance from the manually drawn island edges (Figure S2) using all lidar elevation data within each secondary channel lobe. These profiles were used to investigate changes in the concentration of most elevation gain between the island edges and interiors, and whether the median profile trends were consistent over time and across different channel lobes.

The extensive subaerial exposure captured by lidar enabled the extraction of the geometrical elements of secondary channels. In particular, some secondary channel beds were shallow enough to be exposed for us to measure the depths from the thalweg to the levee tops. This was done by fitting piecewise linear regression to 5m-spaced cross sections along each channel and extracting the fitted positions of the thalweg and the levees (Supporting Information Text S8; Figure S6). For channels where the channel beds were not sampled in lidar, only the widths were captured. In addition, we calculated the sinuosity of secondary channel centerlines and their angle deviation from the primary channel orientation.

### 3.5. Retention potential of secondary channel deposits in deltaic islands

The deposition rate from advection and settling produces an exponential decay along the transport path (e.g., Lamb et al., 2010). Here, we use that idea and fit exponential profiles to the measured accretion rates to solve for the  $e$ -folding transport length scale  $L_t$  [L], in Equation (1) expressed as:

$$\frac{\partial \eta}{\partial t} \propto e^{\frac{-x}{L_t}} \quad (\text{equation 1})$$

where  $\frac{\partial \eta}{\partial t}$  is the accretion rate [L/T],  $x$  [L] is the distance along the secondary channel from the island edge, and  $L_t$  [L] is the  $e$ -folding of the exponential decay equation. We only considered positive  $e$ -folding lengths in profiles that exhibited a decaying accretion trend toward island interiors. Also, to account for any potential imperfect delineation of channel lobes, we varied the lateral distance around each channel and retained the fit with the highest coefficient of determination.

Landforms developed under more rapid settling velocities (e.g., due to coarser grains, enhanced flocculation, or less re-entrainment from the bed) are expected to have smaller  $L_t$ . In the limiting case of no entrainment from the bed,  $L_t$  can be shown analytically (Lamb et al., 2010; Supporting Information Text S9) to be equal to the advection length ( $L_{adv} = \frac{q}{w_s}$ ) where  $q$  is the water discharge per unit width along the flow path [L<sup>2</sup>/T] and  $w_s$  is the settling velocity [L/T].

Secondary channels can extend sediment reach to the interiors of deltaic islands by transporting sediment that would otherwise be deposited and trapped near island edges. However, it remains uncertain whether sediment transported by secondary channels would eventually be trapped on the islands or bypass them entirely. To gauge the retention potential, we fitted Equation (1) to the pointwise 2012-2020 accretion rates versus distance from the island edge and found transport lengthscales for secondary channel lobes ( $L_{t,SC}$ ) and levees ( $L_{t,levee}$ ; Supporting Information Text S7). The estimated transport distances ( $L_t$ ) assume a decaying accretion trend (Equation 1), but it is only an approximation because the decay function does not explicitly account for sediment entrainment. In a vegetated muddy wetland, such entrainment parameterization is nontrivial (Zeichner et al., 2021; Nghiem et al., 2025).

In addition to comparing the  $e$ -folding distance of secondary channels ( $L_{t,SC}$ ) to island sizes, we investigated the effect of grain sizes (e.g., sand versus flocculated mud) on the retention potential of secondary channel deposits. Finer sediments have longer advection lengths than coarse grains (Supporting Information Text S9). For that, we estimated the advection lengths of both mud and sand using the zero-entrainment advection-settling model (Supporting Information Text S9). To calculate the advection lengths of flocculated mud ( $L_{Adv,mud}$ ), we used the median and typical floc settling velocity in WLD, 0.1 mm/s (Nghiem et al., 2024), and the discharge range measured in unchannelized regions in WLD, as reported in Nghiem et al. (2026). For calculating the sand advection length ( $L_{Adv,sand}$ ), we used the same discharge range ( $\sim 0.025$ - $0.090$  m<sup>2</sup>/s; Nghiem et al., 2026) and a settling velocity of 10 mm/s for fine sand.

## 4 Results

### 4.1. Characteristics of the secondary channels

We mapped 116 secondary channels in WLD, of which 106 are single-threaded, and characterized their spatial distribution, geometry, and orientation (Figure 2a-e; Section 3.4). The channels concentrate between about 3 and 7 km from the WLD apex, and 600 m to 3.4 km from the island apexes (Figure 2a). The median and interquartile range of channel lengths are  $\sim 290$  m and  $\sim 163$ - $594$  m. The channels are mostly linear with rare sinuous channels, with an interquartile range of sinuosity of  $\sim 1.0$ - $1.1$  (Figure 2c). Channel widths, measured along several cross sections (Figure 2c; Supporting Information Text S8; Figure S8), have a median and interquartile range of  $\sim 31$  m and  $\sim 19$ - $48$  m, respectively (Figure 2e). Channel depths, measured from V-shaped cross sections (Figure 2c; Supporting Information Text S8; Figure S8), have a median of 18 cm and an interquartile range of 11-28 cm (Figure 2e). As such, width-to-depth ratios have an interquartile range of  $\sim 93$ - $277$  m/m, with a median of  $\sim 162$  m/m (Figure 2e).

Generally, channels are narrower and shallower downstream from the channel heads (Figure 2d). Also, while secondary channels branch from primary channels, with a median angle of  $\sim 64^\circ$  (Figure 2e), some channels bend upstream or downstream, potentially capturing local effects from bidirectional tidal and wind currents. These analyses describe secondary channels as shallow linear channels that mostly terminate at island centers. Besides their geometry, the repeat lidar surveys allowed us to investigate the contribution of secondary channels to the total accretion of deltaic islands.

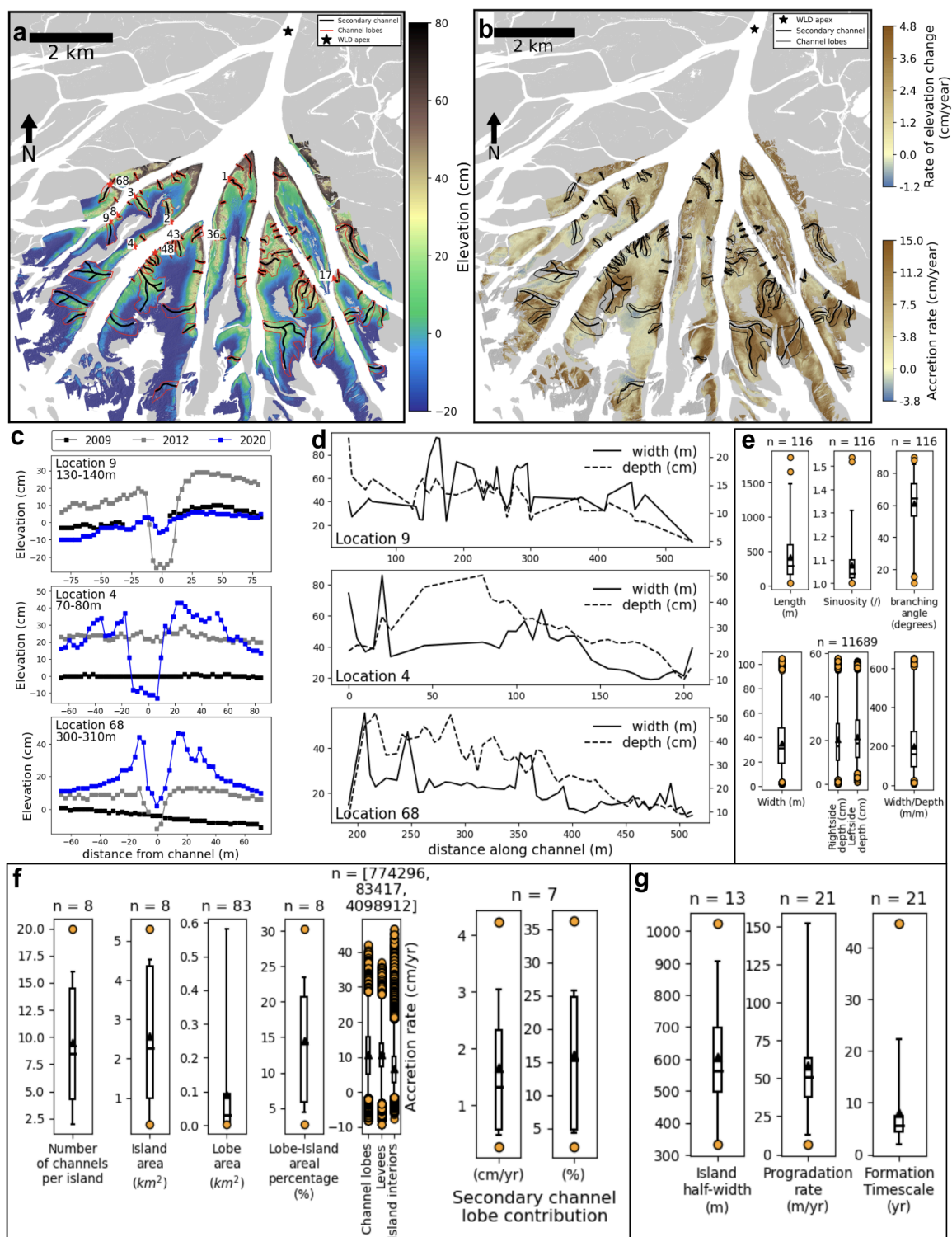
#### *4.2. How much accretion do secondary channel lobes contribute to deltaic islands?*

Evaluating the contribution of secondary channels to deltaic resilience requires analyzing how much sediment they deposit on deltaic islands and whether that is sufficient to keep pace with sea-level rise. To answer this question, we estimated the areal coverage of secondary channel lobes out of the total island area. The total areal footprint shared by the 2012 and 2020 lidar surveys is  $\sim 21.75 \text{ km}^2$  (Figure 2b). Out of the 116 channels, we manually mapped 83 channel lobes (Section 3.2). Active channel lobes occupy approximately  $4.0 \text{ km}^2$ , compared to  $\sim 17.8 \text{ km}^2$  of unchannelized lands, with a median and IQR island area of  $2.3 \text{ km}^2$  and  $1.0\text{--}4.4 \text{ km}^2$ , and a median and IQR lobe area of  $0.24 \text{ km}^2$  and  $0.1\text{--}0.9 \text{ km}^2$  (Figure 2f). While up to 20 channel lobes were mapped on a single island, the median number of active channels per island was 8.5. The median and IQR of the lobe-to-island area percentage are 14.3 % and 5.9-20.7 % (Figure 2f).

Although secondary channel lobes occupy only a limited fraction of the total island area, lidar-derived accretion rates (2012-2020) reveal that their accretion rates were greater relative to those of unchannelized regions (Figure 2f) but comparable to those of levees. The median and IQR accretion rate within channel lobes is approximately 10.5 and  $\sim 5.2\text{--}15.8 \text{ cm/year}$ . In comparison, the accretion rates in unchannelized island interiors are lower, averaging  $\sim 6.3 \text{ cm/year}$  with an IQR of  $\sim 2.7\text{--}10.1 \text{ cm/year}$  (Figure 2f). In contrast, assuming that levees are within 33.4 m of island edges (Section 3.3; Supporting Information Text S7), their median and IQR accretion rates are approximately 10.9 cm/year and 7.2-13.8 cm/year (Figure 2f). The sensitivity of the calculated mean accretion rate of levees to the levee extent ( $L_{t, \text{levee}}$ ) is shown in Figure S5.

Beyond their areal coverage and accretion-rate magnitude, it is most important to estimate whether secondary channel lobes can raise total accretion rates within sediment-starved island interiors to levels comparable to those on levees, and hence to sea-level rise rates. Secondary channel lobes contribute a median of approximately  $\sim 1.3 \text{ cm/year}$  with an IQR of  $0.6\text{--}2.3 \text{ cm/year}$ , which is equivalent to a median of  $\sim 15.2 \%$  and an IQR of 5.0-22.9 % of the median accretion rate at levees, after accounting for the areal lobe-to-island percentage (Figure 2f). These results suggest that deposition within secondary channel lobes can unify accretion from island edges to their centers, but only

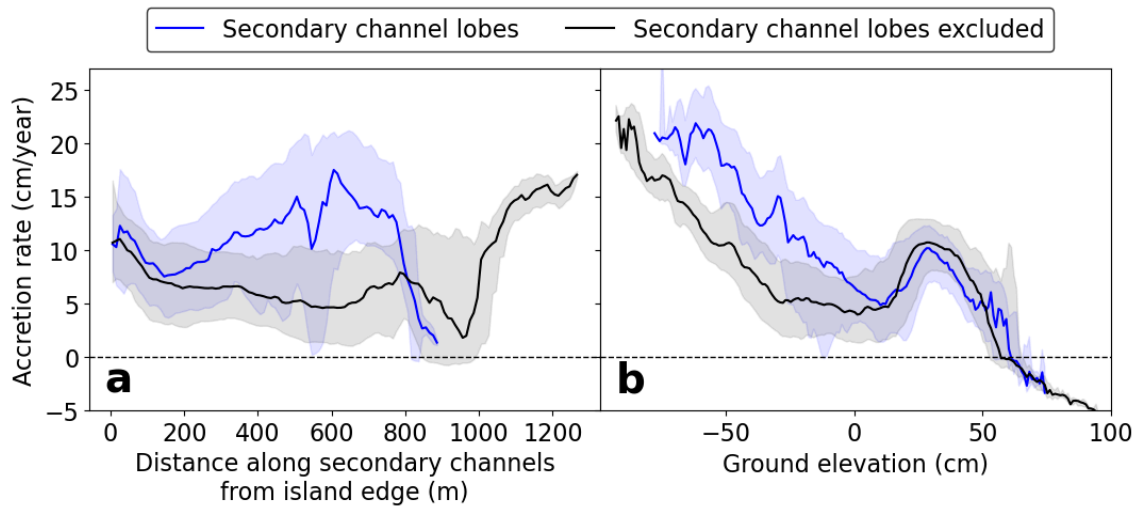
at a segment of the deltaic islands. This variability requires an investigation into whether there is a spatial preference for secondary channel deposition within deltaic islands.



**Figure 2.** Secondary channel morphology and accretion patterns in WLD. (a) 2020 lidar elevation map showing the manually mapped secondary channel centerlines (black

lines) and depositional lobes (red polygons). Numbered annotations identify channel locations referenced in the text and other figures. (b) Maps of the rates of elevation change and accretion between 2012 and 2020. Manually mapped secondary channel centerlines and lobes are shown in black. Accretion is calculated as elevation change corrected for shallow subsidence (Section 3.1; Supporting Information Text S6). (c) Example cross sections showing channel incision and levee buildup. (d) Downstream trends in channel width and depth calculated from cross sections extracted at 5 m intervals. (e) Geometric properties of secondary channels. (f) Attributes of secondary channels, lobes, and deltaic islands, including areas and accretion rates within channel lobes, levees, and island interiors; lobe contribution to island-scale accretion, calculated as lobe accretion multiplied by lobe-to-island areal fraction; and lobe accretion relative to levee accretion. (g) Estimated formation timescales of secondary channel lobes, calculated from island half-widths and lobe progradation rates. In box plots, boxes show medians and interquartile ranges, triangles show means, whiskers show the 1<sup>st</sup>-99<sup>th</sup> percentile ranges, numbers above boxes indicate sample sizes, and orange circles show values outside of the 1<sup>st</sup>-99<sup>th</sup> percentile ranges.

While the overall average rates in secondary channel lobes can match levee aggradation, accretion within these lobes is not uniform across the delta and shows identifiable spatial trends. Secondary channel lobe deposition is enhanced at deeper reaches of island interiors and at lower ground elevations (Figure 2a; Figure 3) as revealed with the analysis of spatial patterns of the 2012-2020 accretion map (Section 3.3). At island edges, binned median accretion rates are ~7-10 cm/year. Farther toward island interiors (within ~800 m), binned median accretion rates increase more than ~15 cm/year within secondary channel lobes, while they decrease to ~5 cm/year in unchannelized areas (Figure 3a). Similarly, while median accretion rates are comparable at ground elevations above ~10 cm, they are higher along secondary channel lobes at lower elevations, reaching ~20 cm/year in low-lying regions (Figure 3b). At distal regions deeper into island interiors (~>1km) and farther downstream, median accretion rates increase again, reaching more than ~15cm/year (Figure 2b; Figure 3).



**Figure 3.** Median binned accretion rates between 2012 and 2020 as a function of (a) distance along secondary channels from island edge (m), and (b) ground elevation (cm). The median and interquartile values are calculated from all accretion rates (2012-2020) after separating them into those outside and those within all mapped secondary channel lobes (Section 3.3).

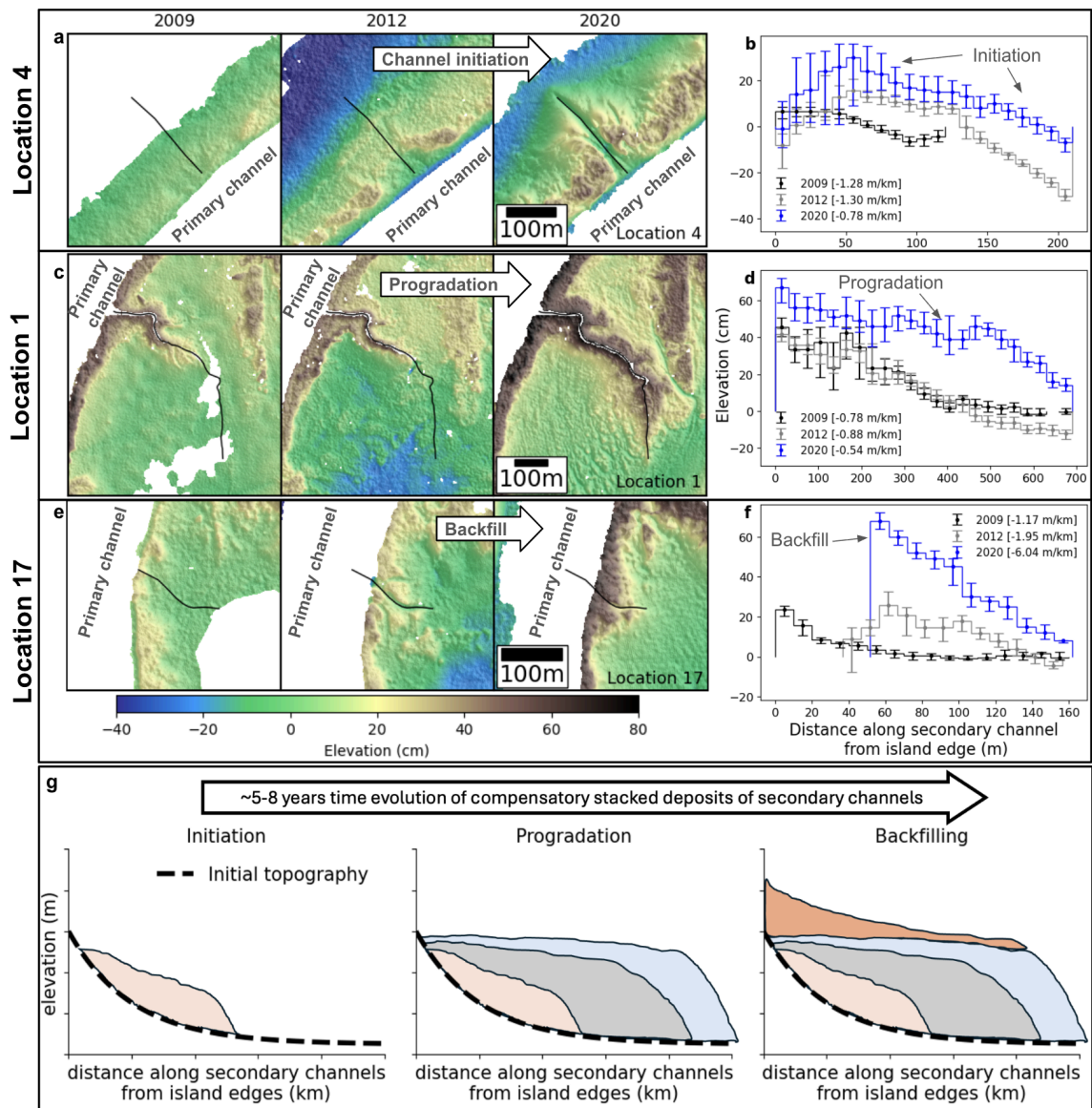
Deposition measured within secondary channel lobes confirms that these channels can raise accretion rates in island interiors to match those of levees. However, deposition between 2012 and 2020 appears to account for only a fraction of the total accretion required in deltaic island interiors. The limited areal extent of this accretion and its spatial variability suggest that the study period captures only a portion of the total contribution of secondary channels to island accretion, as these features are transient and form episodically at different locations, distributing deposition across island interiors over time. Understanding their full potential requires analyzing channel formation over their temporal evolution to estimate a characteristic timescale. We therefore investigate the formation of individual channel lobes over time.

#### 4.3. Description of secondary channel formation cycle

##### 4.3.1. Channel initiation

Repeat lidar surveys (2009-2020) reveal that secondary channels in WLD exhibit spatially variable behavior across different locations. This variability, expressed as differences in deposition patterns along the channels, constitutes distinct stages of a channel-formation cycle, beginning with initiation, followed by progradation, and ultimately by backfilling. As an example of channel initiation, a new channel at location 4 (Figure 2a) incised into the island levees to a depth of approximately 40 to 50 cm (Figure

2c), accompanied by deposition into the island along emerging secondary channel levees (Figure 4a). The secondary channel narrows away from the primary channel, from  $\sim 30\text{m}$  at the island edge to  $\sim 10\text{m}$  width at  $\sim 200\text{m}$  distance toward the island center (Figure 4a-b). The formation of secondary channel levees farther into the island coincides with reduced elevation gain at the channel head (Figure 4b). Accordingly, the elevation profile becomes shallower, from  $-1.28$  and  $-1.30\text{ m/km}$  in 2009-2012 to  $-0.78\text{ m/km}$  in 2020 (Figure 4b). These observations indicate that secondary channels initiate from primary channels through levee incision, followed by localized deposition into the island along the levees of newly formed channel lobes.





**Figure 4.** Temporal evolution of secondary channels shown as (a, c, and e) hillshaded elevation map views, and as (b, d, and f) radially median elevation profiles captured at 2009, 2012, and 2020 lidar surveys at different locations showing different stages of channel development: (a and b) initiation, (c and d) progradation, and (e and f) backfilling. The radially median elevation profiles and elevation gradients (in brackets within the legends) were generated from all elevation data within each manually drawn secondary-channel lobe after being binned into 5% distance intervals as a function of the distance along the secondary channel from the island edge (Section 3.4). The locations for the example secondary channels shown are given in Figure 2a. (g) An illustration of the formation stages of secondary channel lobes (Initiation, Progradation, and Backfilling).

#### *4.3.2. Channel progradation*

Following incision and the establishment of channel levees near the island edges, secondary channels can further prograde into the island, expanding their channel lobes. For example, at location 1 (Figure 1d; Figure 1g; Figure 2a), the channel advanced at  $\sim 60$  m/year toward the island center between 2012 and 2020 (Figure 4c-d). Over this period, binned median elevations increased  $\sim 20$  cm within  $\sim 250$  m of the island edge, and by  $\sim 40$  cm farther into the island, before tapering to  $\sim 25$ - $30$  cm elevation gain toward the island center (Figure 4c-d). Channel gradients also decreased as progradation progressed, from approximately  $-0.78$  and  $-0.88$  m/km in 2009-2012, to  $-0.54$  m/km in 2020 (Figure 4d). Channel width also decreased downstream, from  $\sim 15$ - $30$  m near the island edge to  $\sim 5$ - $10$  m near the terminus (Figure 4c; Figure S8a). At this location, the channel trunk is also generally sinuous, with localized incisions and deposition of overshoot fans in the upstream segments before the channel bends downstream (Figure 4c). Similar progradation patterns are observed along other secondary channels at locations 2 and 3 (Figure 1e; Figure S10). In some cases, progradation is associated with channel deepening and levee aggradation (Figure S8e; Figure S8g). These observations show that progradation is characterized by downstream lobe deposition and declining topographic gradients.

#### *4.3.3. Channel backfill*

While some secondary channels initiated or prograded, others become inactive as deposition becomes concentrated at the island edge rather than farther into the island, leading to closure of the channel head. For example, the secondary channel at location 17 appears to have terminated (Figure 2a; Figure 4e), with a similar pattern observed at another location (Figure S11). While the channel lobe experienced  $\sim 20$  cm elevation gain in 2009-2012, most of the elevation gain in 2012-2020, approximately  $\sim 30$ - $40$  cm, occurred near the island edge, with reduced elevation gain farther into the island (Figure

4f). These changes are reflected in the topographic gradient of the channel lobe, which becomes steeper from  $\sim -1.33$  m/km in 2009 to  $-5.86$  m/km in 2020 (Figure 4f). These observations show that channel termination is characterized by deposition focused near the island edge, reduced inland accretion, and steepening of the lobe profile.

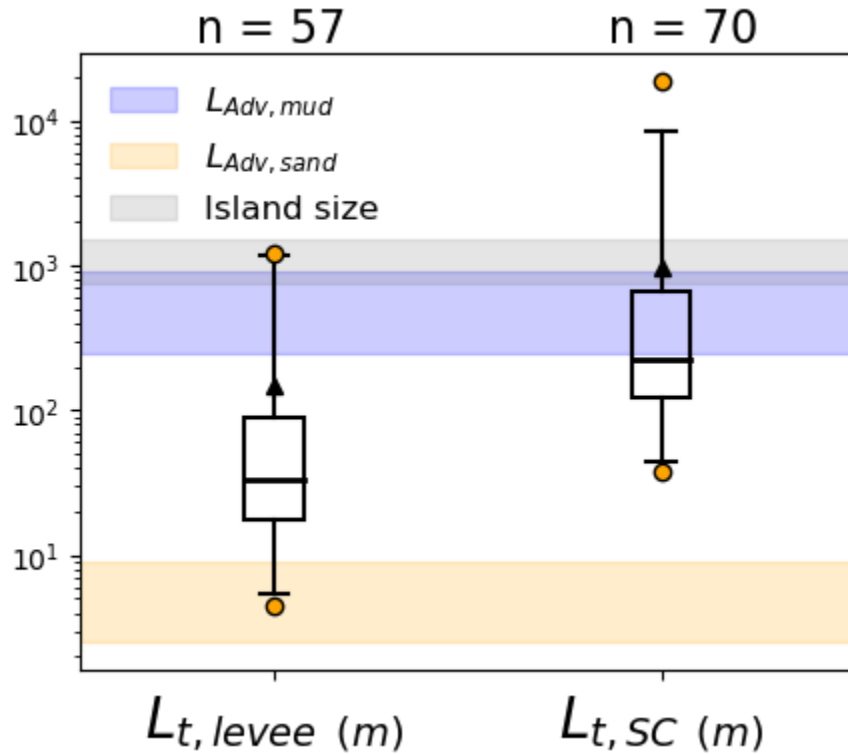
The range of stages observed among secondary channel lobes across WLD suggests that they represent different phases of a recurring formation cycle. Of the 96 analyzed channels, 33 ( $\sim 34\%$ ) were incised into islands between 2009 and 2020, whereas 21 ( $\sim 22\%$ ) prograded. In contrast, 42 channels ( $\sim 44\%$ ) were backfilled, with most sediment deposited at the island edge and reduced elevation gains toward the island interiors. Together, these observations indicate that secondary channels initiate through incision into island levees, forming narrow channels with localized deposition along their banks (Figure 4a-b; Figure 4g). Following initiation, channels prograde farther into island interiors, accompanied by sediment deposition that progressively shifts inland (Figure 4c-d; Figure 4g). During this stage, topographic gradients become shallower, elevation gain increases along the channel lobe, and channel morphology becomes more complex, including meandering trunks and overshoot fans (Figure 4c; Figure S10). Eventually, channels are backfilled as primary channel levees extend along island edges, leading to closure of channel heads and enhanced sediment accumulation at the island edge relative to areas farther inland (Figure 4e-f; Figure 4g). These results suggest that secondary channels across the delta progress through a characteristic sequence of initiation at island edges, progradation to island centers, and backfilling.

Assuming that each channel lobe exhibits a single stage of repeated cycles, we estimated the timescale at which these cycles terminate. Secondary channel lobes are likely constrained by island size, which can be approximated by island half-width (Edmonds et al., 2011; Salter & Lamb, 2022). The median island half-width is  $\sim 564$  m, with an interquartile range of 496-697 m. Based on 21 secondary channels that prograded between 2012 and 2020, the median progradation rate is  $\sim 50$  m/year, with an interquartile range of  $\sim 38$ -63 m/year. At these rates, secondary channel lobes would require a median of  $\sim 6$  years to prograde from island edges to island centers, with an interquartile range of  $\sim 5$ -8 years (Figure 2g). The observed progradation rates suggest that secondary channel lobes can raise the accretion rates of island interiors to those of levees within sub-decadal timescales.

#### *4.4. Retention of sediment transported by secondary channels*

While secondary channels progressively entrain sediment and have higher discharge rates (Nghiem et al., 2026), thereby increasing accretion in island interiors, it remains uncertain whether this sediment is ultimately retained within the islands. The median transport distance ( $L_{t,SC}$ ) derived from accretion profiles of 70 secondary channel lobes (Figure S12; Section 3.5) is 229 m, with an interquartile range of 126-662 m (Figure

S12b). These values indicate that secondary channels extend sediment transport much farther inland than unchannelized regions, for which the inverted  $L_{t,levee}$  has a median of 33.4 m and an interquartile range of 17.3-87.9 m (Figure 5; Supporting Information Text S7). Because most  $L_{t,SC}$  values remain mostly smaller than island sizes in WLD (~750-1500m; Figure 5), this suggests that a substantial fraction of sediment deposited in secondary channel lobes is retained within island boundaries. However, retention appears variable. While it is expected that the accretion trend toward island interiors would be positive during the progradation stage (Figure 4d), several channel lobes have almost flat accretion profiles with  $L_{t,SC}$  that exceed island sizes (>2000 m; Figure 5; Figure S12), implying lower retention within the islands. One possible explanation for this variability is variability in sediment settling velocity, which is primarily controlled by grain size and mud flocculation. Indeed,  $L_{t,SC}$  values from channel lobes are closer to the advection lengths of flocculated mud in unchannelized regions in WLD, ~250-900 m, than those of sand, ~2.5-9.0 m (Section 3.5; Supporting Information Text S9), suggesting that at least some channel lobes have coarser sediment than the typical muddy deltaic island deposits of WLD, as described by Nghiêm et al. (2025, 2026). In addition,  $L_{t,SC}$  may vary through time within individual channel lobes, as the flattening of topographic gradients of channel lobes (Figure 4b; Figure 4d) could reflect grain size fining and longer transport distance  $L_{t,SC}$ . These results suggest that secondary channels enhance sediment delivery into island interiors, but retention varies among lobes and may depend on grain size.



**Figure 5.** Comparison between levee extents ( $L_{t,levee}$ ) inverted from accretion rate profiles in unchanneled regions, secondary channel transport lengths ( $L_{t,SC}$ ) inverted from accretion rate data in channel lobes, and advection lengths of mud ( $L_{Adv,mud}$ ) and sand ( $L_{Adv,sand}$ ). In box plots, boxes show medians and interquartile ranges, triangles show means, whiskers show the 1<sup>st</sup>-99<sup>th</sup> percentile ranges, numbers above boxes indicate sample sizes, and orange circles show values outside the 1<sup>st</sup>-99<sup>th</sup> percentile ranges.

## 5 Discussion

Because repeat lidar maps elevation over large subaerial regions, it provides valuable information about the contribution of secondary channels to deltaic islands, compared to spatially limited field measurements, e.g., feldspar horizon markers or OSL measurements (Rowland et al., 2005). Not only do secondary channels transport sediment to sediment-starved island interiors, but deposition at channel lobes occurs at rates comparable to levee aggradation. The higher accretion rates within secondary channel lobes compared to levees (Figure 3a) are similar to previous studies that found enhanced accretion rates along secondary channels in WLD (4-5 cm/year compared to a 0.6 cm/year delta-averaged rate of elevation gain; Smith et al., 2020; Olliver & Edmonds, 2017). Similarly, OSL dating observations in Bayou Lafourche suggest that episodic

deposition along crevasse splays can reach 1-4 cm/year, preserving more than 75% of incoming suspended sediment (Shen et al., 2015; Esposito et al., 2017). Still, when accounting for areal coverage, secondary channels seem to only contribute to a fraction of the total island accretion.

Our estimate of the total accretion within secondary channel lobes suggests that there is still ~85% deficit for deltaic islands to aggrade uniformly and match the rate of sea level rise. Extreme events, such as storms, hurricanes, and major floods, may help bypass densely vegetated levees and raise accretion rates within island interiors (Bevington et al., 2017; Kenney et al., 2022). Locally, organic matter production can also raise accretion rates (Bevington & Twilley, 2018; Smith et al., 2020). Still, because we use levee aggradation as a reference and in the rapidly growing Wax Lake delta, such a rate may exceed sea level rise (Jankowski et al., 2017), the estimated secondary channel contribution may be understated. Similarly, the calculated levee accretion rate depends on the segmentation we applied to unchannelized regions, as shown by the sensitivity analysis of levee extent delineation (Supporting Information Text S7). It is also possible that the total accretion rates delivered by secondary channels were underestimated because they were limited to distinguishable lobate landforms (Section 3.2).

The remaining contribution of secondary channels to island accretion is likely not confined to mapped channel lobes, but may also be distributed more broadly across island surfaces as sediment drapes. Inverted transport distances from secondary channel lobes indicate that these secondary channels supply sediment farther into islands than predicted by the advection-settling model (Figure 5; Supporting Information Text S9), which can be attributed to faster flows and entrainment in secondary channels (Nghiem et al., 2026). By extending sediment reach, secondary channels could both redistribute sandy sediments farther into island interiors, which is favorable for deltaic land building (Kim et al., 2009), and deliver muddy sediment beyond lobe boundaries as drapes. This interpretation is supported by the inverse correlation between fitted  $L_{t,SC}$  and  $R^2$ , such that channel lobes with larger  $L_{t,SC}$  produce poorer fits to the log-linear decay relation (Equation 1; Figure S12b). It is also consistent with the flattening of topographic gradients following initiation and progradation (Figure 4b; Figure 4d), and may help explain the upward-fining trend observed in WLD stratigraphy (Smith, 2014; Nghiem et al., 2026). However, mud is barely contained within islands (Figure 5), and with repeated secondary channel re-entrainment, less mud is likely to be preserved on the islands.

Nonetheless, the observation that secondary channel lobe deposition did not occupy large areas simultaneously during 2009-2020 does not imply a limited cumulative contribution to island accretion. Rather, the time-integrated effect of lobe deposition may sustain island interiors through repeated, spatially shifting depositional events. As such, secondary channels may produce compensatorily stacked lobes (Straub et al., 2009; Carlson et al., 2018), in which successive deposits form in different interior

locations through time. This interpretation is supported by amplified lobe accretion in the most sediment-starved regions of island interiors and at topographic lows (Figure 3), where sediment supply is limited. A similar spatial pattern has been reported from crevasse splay in the Balize delta, where accretion rates measured using feldspar marker horizons ranged from  $0.64 \pm 0.07$  cm/year in elevated, vegetated areas to  $9.36 \pm 3.07$  cm/year in open-water settings, indicating a stronger deposition in lower regions with more accommodation space (Cahoon et al., 2011).

This compensatory pattern is consistent with secondary channels acting as transient, autocyclical features that deposit at different locations during different periods. Enhanced accretion in the most sediment-starved regions supports the autogenic activation of secondary channel initiation and aggradation (Figure 2b; Figure 3). In turn, the spatial variability observed across channel lobes in WLD is consistent with an auto-cyclical behavior predicted by numerical models (Nienhuis et al., 2018; Salter & Lamb, 2022), in which channels undergo repeated cycles of initiation, progradation, and backfilling within decadal timescales (Salter & Lamb, 2022). In the first stage, decay of accretion toward island interiors produces higher levees and steeper water-surface slopes, driving water and sediment flow toward island interiors; increased flow depth at island levees enhances entrainment while reducing deposition upstream, corresponding to channel initiation (Figure 4g). In the second stage, enhanced sediment flux promotes progradation into island interiors, reflected in rapid channel advancement rates (Figure 4g). In the third stage, reduced flow depth over aggraded interiors limits sediment transport inland, while increased sediment concentrations upstream enhance deposition at channel heads, leading to backfilling (Figure 4g). After backfilling, the cycle may re-initiate until a uniform accretion is achieved from the island edge to its center. After which, a new channel and a new cycle initiate at another sediment-starved topographic low. Although our calculations suggest that a full formation cycle may occur within roughly a decade, this estimate likely understates the true duration of such a cycle because we do not observe the full sequence, from initiation at the island edge to progressive progradation to the island center, until a uniform accretion is reached within the ~11-year study period (2009-2020). This discrepancy may indicate hiatuses between stages, and it remains unclear whether individual channel lobes pass through one or multiple formation cycles. Nevertheless, these observations suggest that secondary channels provide an efficient mechanism for redistributing sediment beyond levees and into island interiors as compensatorily stacked lobes.

## 6 Conclusion

Lidar-derived accretion along secondary channel lobes indicates that these channels play a primary role in delivering sediment to island interiors in WLD (2009-2020), enabling land-building rates (10.5 cm/year) to match levee aggradation (10.9 cm/year), within subdecadal timescales. When accounting for the median lobe-to-island area percentage

of 14.3 %, channel lobes contribute ~15.2 % of the necessary accretion rate to match levee aggradation rates, with more deposits likely draped over island interiors. Our observations show that secondary channels are transient autogenic features that initiate, prograde, and backfill, with enhanced accretion in regions most starved of sediment, such as low-lying distal island interiors. Our findings suggest that secondary channels replenish island interiors with compensatory stacked lobes.

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## Supporting Information

### Text S1. Lidar Processing - spatial references

We use lidar surveys acquired in 2009, 2012, and 2020 in WLD to map elevation and elevation change. The surveys were acquired on January 14–15, 2009 (2.03 pt/m<sup>2</sup>; vertical uncertainty 5.5 cm; Wagner et al., 2017), December 18, 2012 (2.04 pt/m<sup>2</sup>; vertical uncertainty 8.6 cm; NOAA, 2015), and November 18, 2020 (19.16 pt/m<sup>2</sup>; vertical uncertainty 1.3 cm; Nghiem, 2022). These datasets were selected because they capture relatively high subaerial exposure, compared to other lidar surveys in WLD. All lidar datasets were converted to a common reference frame (NAD83 (2011), NAVD88 (GEOID18) using NOAA VDATUM software.

### **Text S2. Lidar Processing - vertical co-registration**

For an accurate lidar differencing, we used vertical co-registration to remove global offsets introduced by regional subsidence and the error associated with calibrating lidar return positions to GPS stations. This procedure was done by calculating elevation differences at six stable benchmark structures across WLD. The pointwise elevation differencing was performed using the Multiscale Model-to-Model Cloud Comparison (M3C2; Lague et al., 2013) tool in CloudCompare, with a 0.5 m projection depth and a 10 m search diameter. Next, to eliminate outlier elevation-difference measurements (e.g., at structural edges), we used an unsupervised outlier-detection method (Isolation Forest). After calculating the mean elevation differences at each structure, we used the mean across all structures as the vertical co-registration length, applied uniformly to lidar elevations. The consistency of structure-wise mean elevation differences within one standard deviation of each other supports our assumption of spatially uniform elevation offsets. Using the 2020 survey as a reference, the 2009 and 2012 datasets were vertically adjusted by -1.5 cm and -10.3 cm, respectively.

### **Text S3. Lidar Processing - removal of water returns**

While the other lidar surveys had water returns classified and removed, the 2009 lidar did not. For that, we first used an NDVI-based land mask derived from a Landsat image, acquired on January 12, 2009, to roughly separate water from land returns. Due to the relatively coarse Landsat resolution, 30m, returns between water and land were misclassified. To that end, in addition to return intensity, we calculated several point-wise covariance features using the PDAL library (Butler et al., 2021; PDAL contributors, 2022), including planarity, linearity, scattering, and point density. These features, along with the initial Landsat-derived rough classification and lidar parameters (e.g., intensity, elevation, flightline ID), helped an XGBoost classifier more efficiently separate water from land returns from the coarse land mask.

### **Text S4. Lidar Processing - removal of vegetation returns**

For each survey, we applied a rigorous ground-filtering workflow to remove low-lying vegetation. To preserve geomorphic features such as levees, which are often misclassified by relief-based vegetation filters, we first computed a verticality metric to remove near-vertical structures prior to vegetation filtering. Vegetation was removed using the Cloth Simulation Filter (CSF; Zhang et al., 2016), with grid resolutions of 30 m (for 2009 and 2012 lidar) and 10 m (for 2020 lidar), and a relief threshold of 6 cm. Removed points were iteratively reclassified using a relief threshold (3 cm) and angle thresholds (starting with 0.3° to 2.0°).

### **Text S5. Calculations of point-wise and gridded elevation and elevation differences**

Elevation differences in WLD were mapped by differencing the filtered ground lidar returns, then gridding the results to generate elevation maps. Point-wise elevation differences were calculated with the M3C2 algorithm (Lague et al., 2013) in CloudCompare. A 5 m diameter was used to compute mean elevations, and points with fewer than four neighbors were excluded. To extract and analyze elevation and elevation-change profiles, we used point-wise measurements. In comparison, to calculate total change volumes, we used a gridded version. The lidar elevation changes for each lidar pair were gridded using inverse distance weighting into structured maps with a 2-meter resolution over the domain 637,950 E to 662,050 E and 3,251,950 N to 3,271,050 N (UTM).

#### **Text S6. Estimating accretion from elevation changes**

After calculating elevation differences, we applied a correction to separate shallow subsidence from accretion and generate WLD accretion maps. The correction was calculated from a linear fit of field-measured accretion thickness (cm) to the offset between elevation-difference measurements and accretion. The offset was assumed to represent shallow subsidence (cm) (Cahoon et al., 1995; Jankowski et al., 2017; Lynch et al., 2015). We acquired these measurements from CPRA (2022), which were collected at the CRMS station, CRMS0479. The linear fit had a slope of  $0.68 \pm 0.01$  and an intercept of  $0.00 \pm 0.19$ , suggesting that shallow subsidence accounted for approximately 68% of the overburden accretion. We applied this correction across the delta to calculate accretion from the measured elevation changes. Although shallow subsidence varies spatially due to several parameters that vary across space, e.g., grain-size packing, hydraulic conductivity, and organic-matter compressibility, we believe this correction is a reasonable starting point for mapping accretion in WLD.

#### **Text S7. Estimation of the levee extent**

To calculate the characteristic levee extent ( $L_{t,levee}$ ), we first drew 65 transects in different regions of WLD perpendicular to the primary channel and extending from before the island edges to the island centers. The transects were drawn in regions from secondary channel lobes, where there were 2020 elevation and 2012-2020 accretion data extending from the island edge to the island interiors. Next, along each transect, we sampled at 1.0 m intervals. At each transect point, we interpolated all lidar elevation (2020) and pointwise accretion measurements (2012-2020) within a 5 m radius, and used inverse-distance weighting to calculate the mean elevation and accretion. Using the accretion rates against profile distances from the first data point at the island edges, we fit a linear regression model in log-linear space and calculated the coefficient of determination ( $R^2$ ) and the  $e$ -folding distance, similar to Equation (1). We iteratively varied the profile distance cutoff, starting with 5m from the island edge to the total distance at the island centers, and selected the  $e$ -folding distance with the highest  $R^2$ .

(Figure S3). We rejected calculations with negative  $e$ -foldings, leaving only 57 of the 65 transects with valid  $e$ -folding distance calculations. The median fitted  $e$ -folding distance was chosen as the levee extent ( $L_{t,levee}$ ) and used to isolate and calculate the mean accretion rate of levees, excluding regions beyond the levee extent ( $L_{t,levee}$ ) from the island edges. The median of  $e$ -folding distance ( $R^2$ ) and cutoff distances are 33.4 m, 0.92, and 27.0 m, respectively, and their interquartile ranges are 17.3-87.9m, 0.82-0.96, and 9.0-61.0m (Figure S4). We noticed that in several cases, the optimal  $e$ -folding distance extended beyond the distance cutoff.

#### **Text S8. Extraction of widths and depths of secondary channels**

The widths and depths of secondary channels were automatically measured from the elevation cross-sections along each channel (Figure S6). For each lidar return, we calculated its channel identification based on the channel lobe it fell within, the distances of each lidar return within a specific secondary channel lobe from that channel centerline, the side of the return to the downstream orientation of the channel centerline, and the orthogonally projected distance along the channel starting from the channel head at the island edges. The side of lidar returns relative to the channel centerlines was defined as whether the point is to the right of the downstream orientation of the channel centerline or to its left. For each channel, using all lidar returns with their elevation information and the calculated lateral and downstream distances, we extracted cross sections at 5m-spaced segments downstream of the channel head (Figure S6a). For each cross-section (Figure 2c), we fitted a piecewise 4-line linear regression to the elevation-lateral distance relationship (Figure S6b). From the edges of the four fitted lines, the positions of the thalweg and two levee tops were extracted, which were used to calculate the channel widths and two depth measurements. For channels without channel beds, the width was calculated as the distance between the two closest points on the right and left sides of the channel centerline. Cross sections with no lidar returns along the channel bed were identified by whether the fitted lines resembled a conventional channel cross section (Figure 2c; Figure S6b); the second and third lines had negative and positive gradients, respectively. In addition, any fitted information with width measurements lower than 2m was rejected.

#### **Text S9. The advection-settling model and advection lengths**

Deposition of advected suspended sediment by overbank flow from primary channels, and of sediment sourced from them, can be modeled from the island edges to their centers using the advection-settling model, as derived by Zeichner et al. (2012; Equation S1). The advection-settling model assumes sediment transport without entrainment and the decay of the sediment concentration; hence, the accretion rate is a function of

distance from the sediment source at the island edges. The model can be derived assuming no grain-size specific influence, starting with mass balance, as follows:

$$\frac{\partial q_s}{\partial x} = w_s (e_s - c_b) \quad (\text{equation S1a})$$

where  $q_s$  the volumetric sediment discharge per unit width [ $L^2/T$ ],  $x$  is the distance from the island edge to its center ( $L$ ),  $w_s$  is the settling velocity [ $L/T$ ],  $e_s$  is the bed entrainment rate, and  $c_b$  is the near-bed sediment concentration.

Without entrainment and without turbulent diffusion,  $e_s$  can be approximated as zero and  $q_s$  can be expressed as  $q_s = \underline{c}q$  where  $\underline{c}$  is the depth-averaged sediment concentration and  $q$  is the water discharge per unit width [ $L^2/T$ ]. Under these assumptions, sediment concentration can be expressed after integrating Equation (S1a) as:

$$\underline{c} = c_0 \exp\left(-\frac{r_0 w_s}{q} x\right) \quad (\text{equation S1b})$$

where  $c_0$  is the sediment concentration at the island edge, and  $r_0$  is the ratio of depth-averaged to near-bed concentration (Parker et al., 1987). By differentiating Equation (S1b) and multiplying by  $q$ , sediment flux divergence can be expressed as:

$$\frac{\partial q_s}{\partial x} = -r_0 w_s c_0 \exp\left(-\frac{r_0 w_s}{q} x\right) \quad (\text{equation S1c})$$

Using the Exner formulation of bed elevation evolution as a function of sediment flux divergence, the accretion rate can be expressed as:

$$(1 - \lambda) \frac{\partial \eta}{\partial t} = -\frac{\partial q_s}{\partial x} \quad (\text{equation S1d})$$

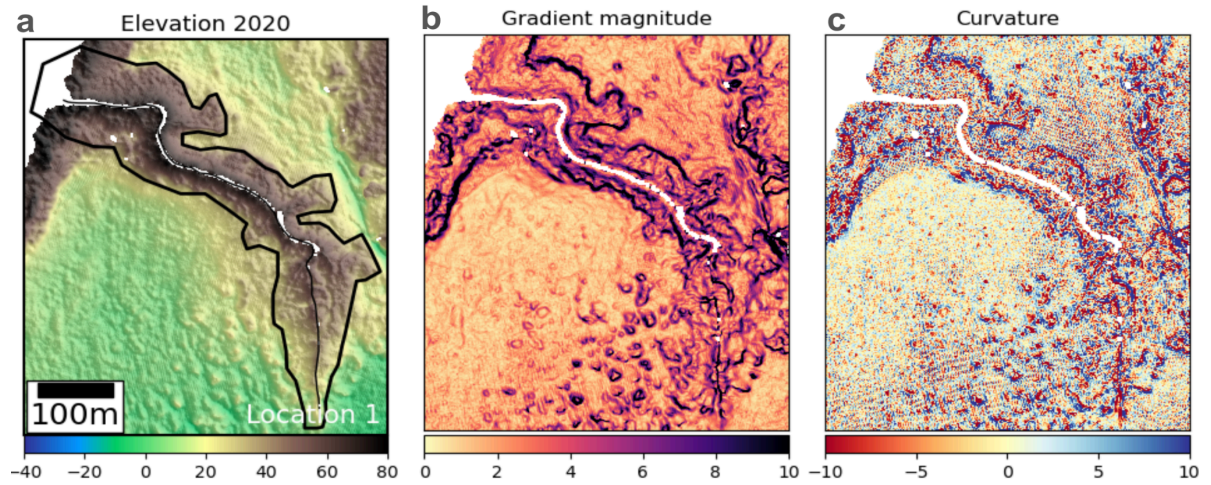
where  $\lambda$  is the porosity of accreted deposits,  $\eta$  is the island ground elevation, and  $t$  is time. Substituting Equation (S1c) in (S1d) gives the following formulation of the advection-settling model:

$$\frac{\partial \eta}{\partial t} = \frac{c_0 r_0 w_s}{(1-\lambda)} \exp\left(-\frac{r_0 w_s}{q} x\right) \quad (\text{equation S1f})$$

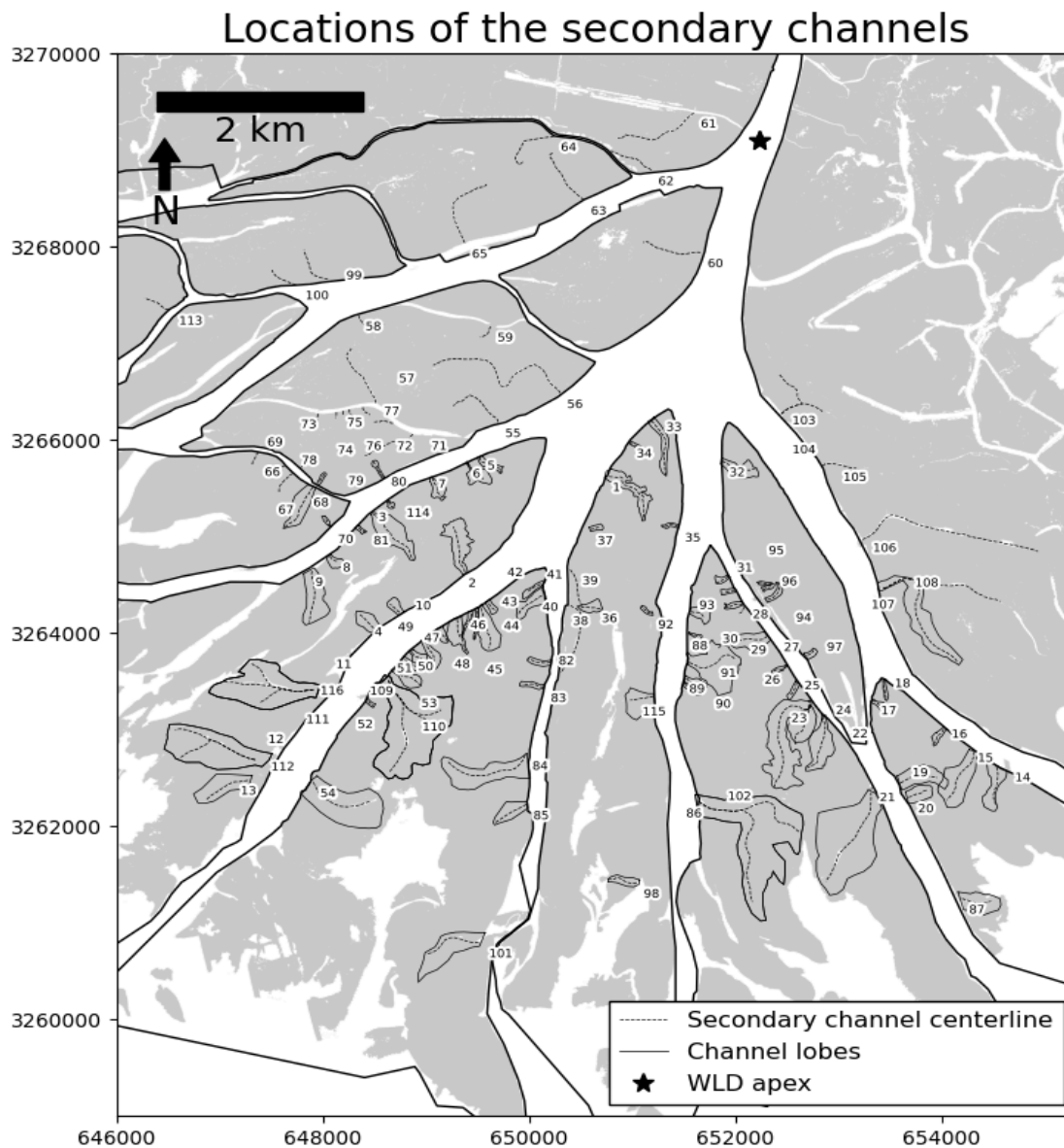
in which  $\frac{\partial \eta}{\partial t}$  is the accretion rate [ $L/T$ ]. The value  $\frac{q}{r_0 w_s}$  defines a characteristic length scale, termed the advection length (Lamb et al., 2010; Ganti et al., 2014). This advection length can be used to estimate the sediment reach due to overbank flows, assuming no



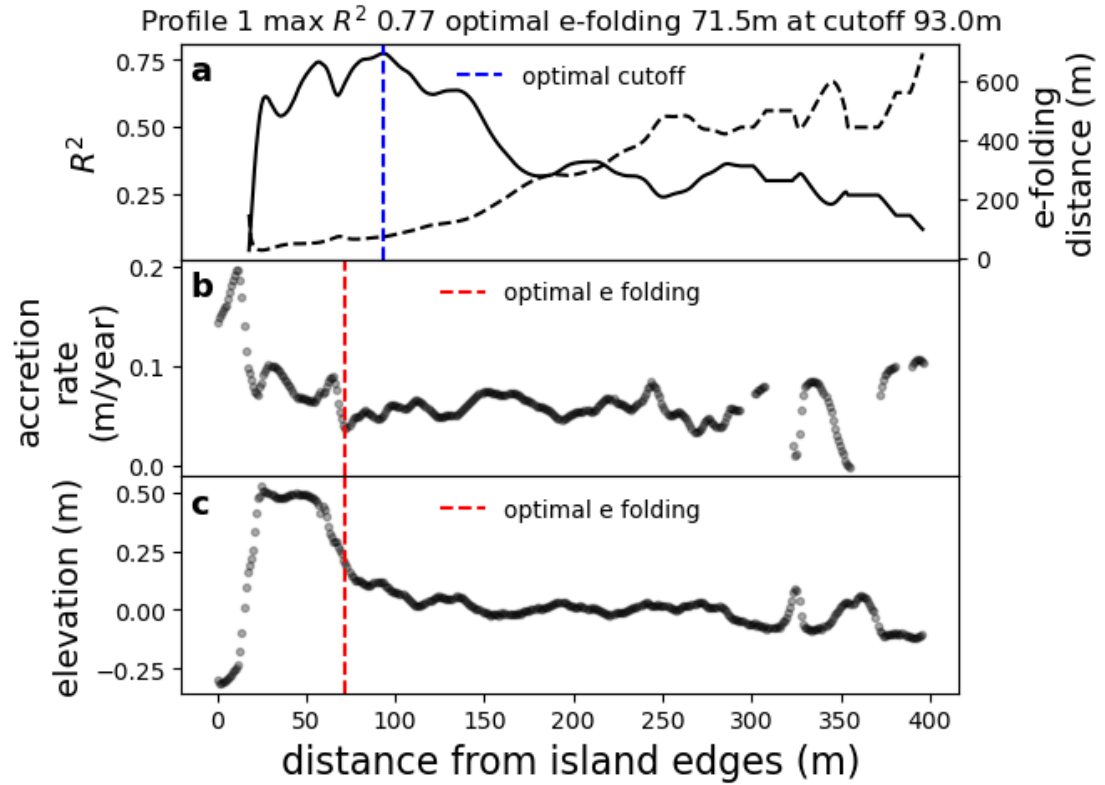
entrainment. In a well-mixed water column,  $r_0$  can be approximated as 1, reducing the advection length term to be dependent on settling velocity and water discharge  $\frac{q}{r_0 w_s}$ .



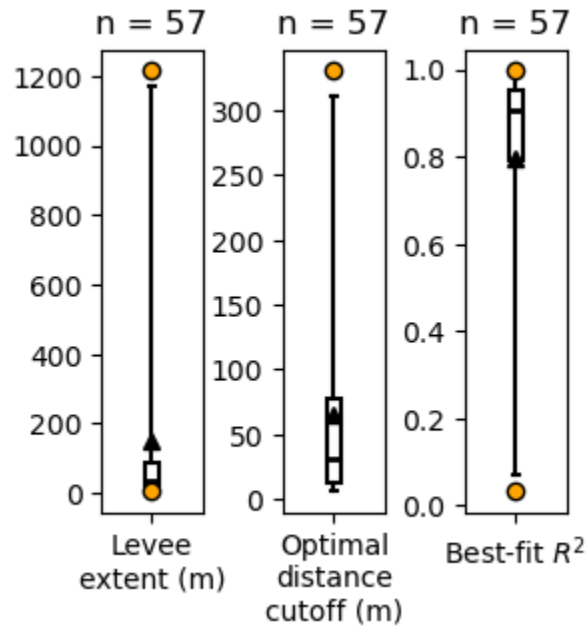
**Figure S1.** Map view of manually drawn secondary channel lobe, in a) elevation, b) gradient magnitude, and c) curvature. Here, the gradient and curvature were calculated using a 3-pixel window.



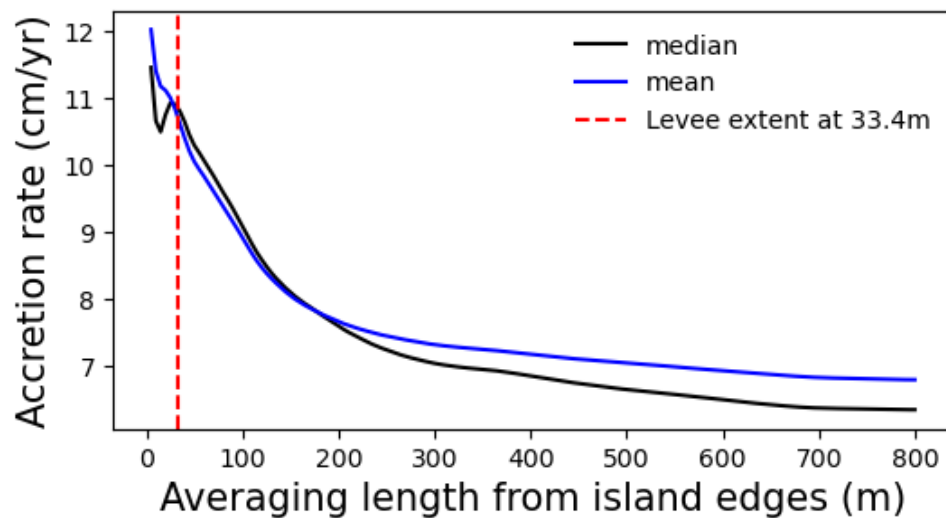
**Figure S2.** Location map of secondary channels with numbers at their channel heads. Gray color represents subaerial lands. The delta apex is shown as a black star and located at UTM coordinates 652230E, 3269100N (following Wagner et al., 2017).



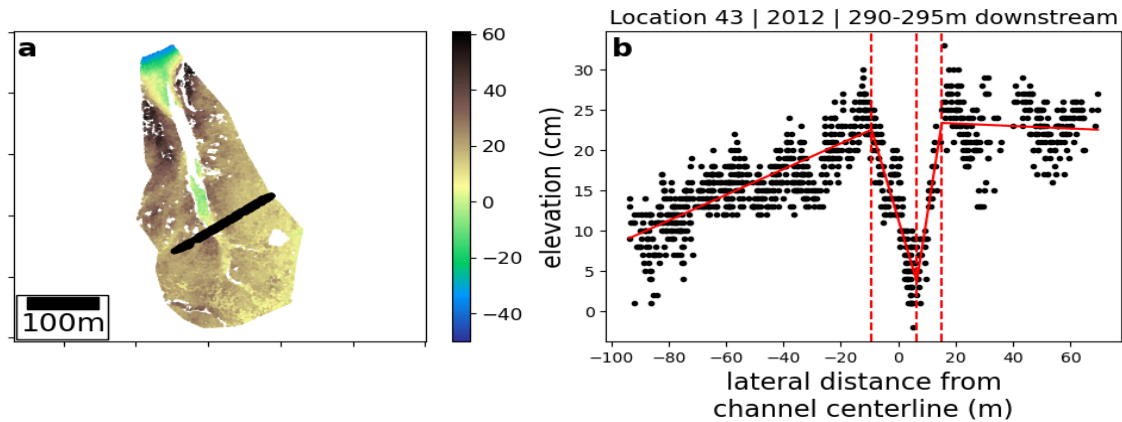
**Figure S3.** An example of levee extent ( $L_{t,levee}$ ) extraction from fitting the exponential decay model on accretion rates along a transect profile perpendicular to unchannelized levees, showing (a) the coefficient of determination and fitted  $e$ -folding distances as a function of the cutoff distances starting from the island edges. Solid curves correspond to  $R^2$  values, while dashed curves correspond to the inverted  $e$ -folding distance. (b) the accretion rate profile, and (c) the elevation profile. The distance cutoff and  $e$ -folding distance associated with the highest  $R^2$  are displayed as dashed vertical lines.



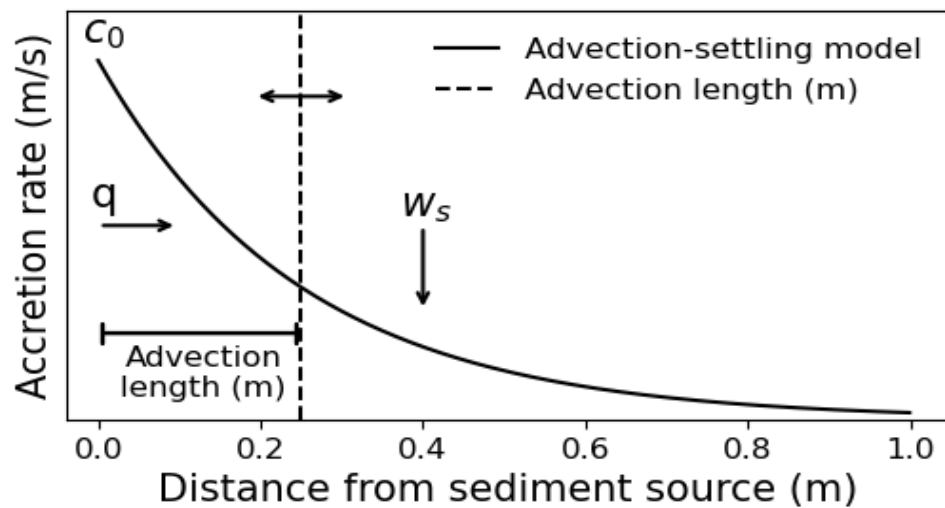
**Figure S4.** Boxplots of the levee extent ( $L_{t,levee}$ ), optimal distance cutoffs, and best-fit  $R^2$  produced by log-linear fits of accretion rate versus distance from island edges at the unchannelized regions transects perpendicular to levees. In box plots, boxes show medians and interquartile ranges, triangles show means, whiskers show the 1<sup>st</sup>-99<sup>th</sup> percentile ranges, numbers shown above boxes indicate sample sizes, and orange circles show values outside the 1<sup>st</sup>-99<sup>th</sup> percentile ranges.



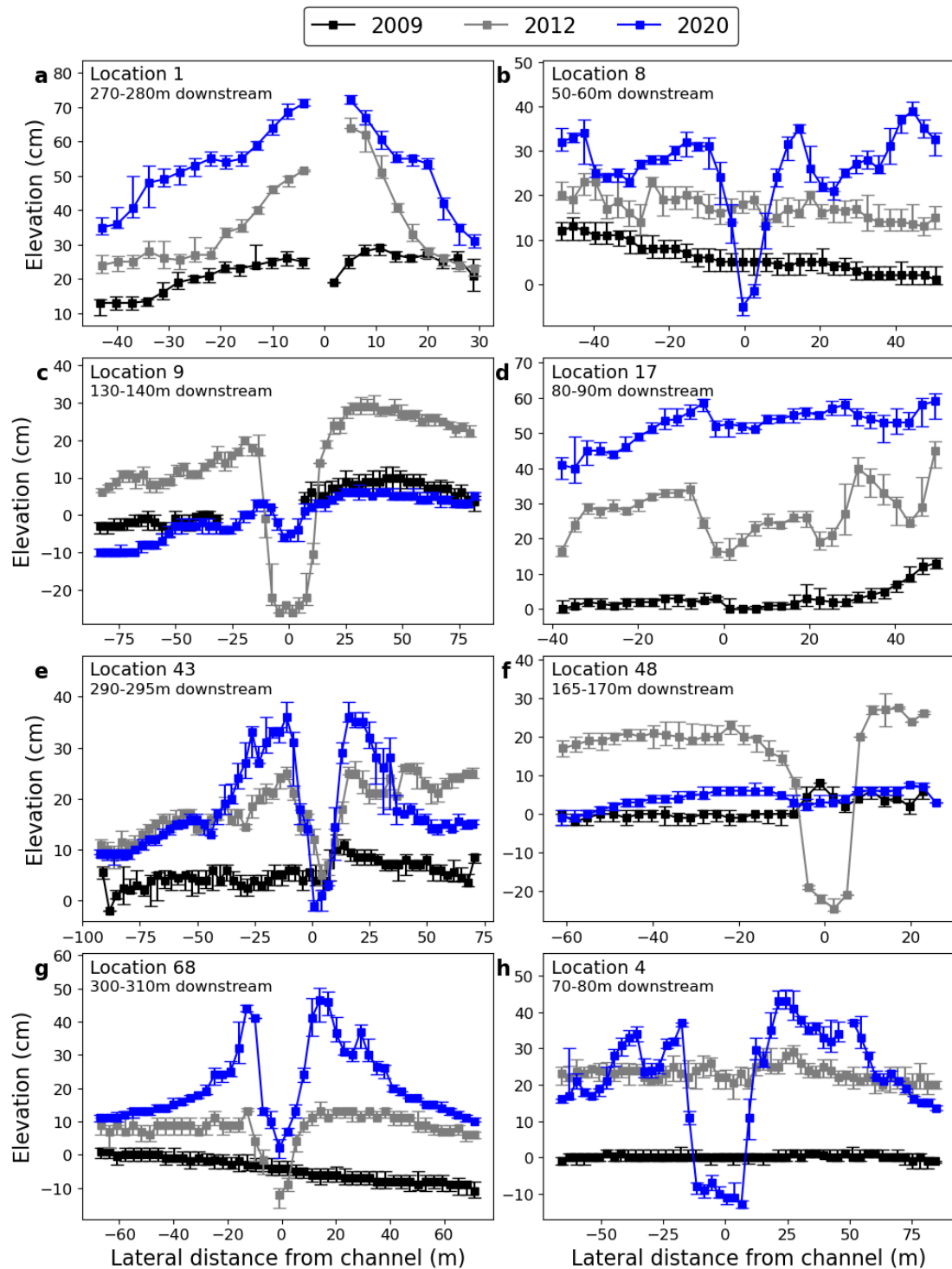
**Figure S5.** Sensitivity analysis of the mean and median accretion rates (cm/year; 2012-2020) calculated from all map regions as a function of the total averaging distance starting from island edges. Also shown is the median  $e$ -folding distance fitted from unchannelized-region transects, which is chosen as the characteristic levee extent ( $L_{t,levee}$ ). The accretion rate at this levee extent is chosen as the representative accretion rate of levees.



**Figure S6.** Extraction of widths and depths of secondary channels from their cross sections. (a) Map view of 2012 elevation data within the secondary channel lobe at location 43. (b) Cross-section of the channel taken from the lidar returns between 290 and 295m downstream from the channel head at the island edge. Black dots in panel (a) show the data source for the cross-section in panel (b). The continuous red lines show the fitted piecewise linear regression model, with breakpoints marked by vertical red dashed lines delineating the thalweg and channel banks.



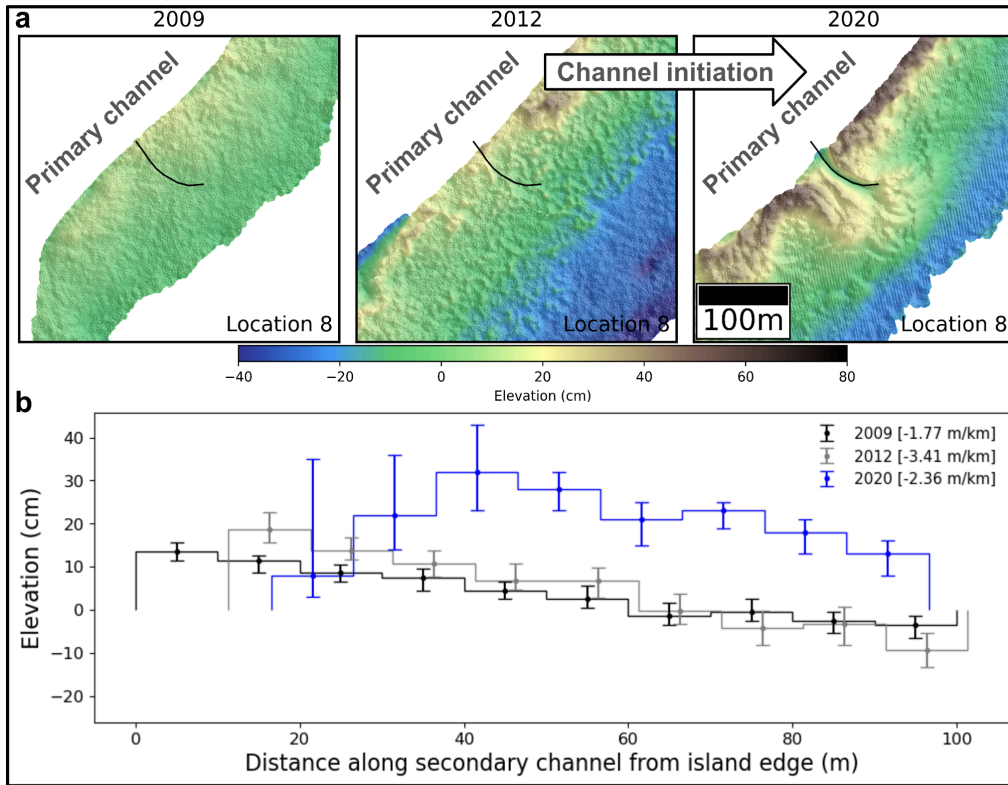
**Figure S7.** An illustration of the exponentially decaying accretion profile as predicted by the advection-settling, showing the extent of the advection length. The parameters  $c_0$ ,  $w_s$ , and  $q$  are, respectively, the sediment concentration at the island edge, sediment settling velocity, and water flow.



**Figure S8.** Cross-section transects taken orthogonal to several secondary channels from the three lidar surveys, 2009, 2012, and 2020. The elevation profiles are mean values

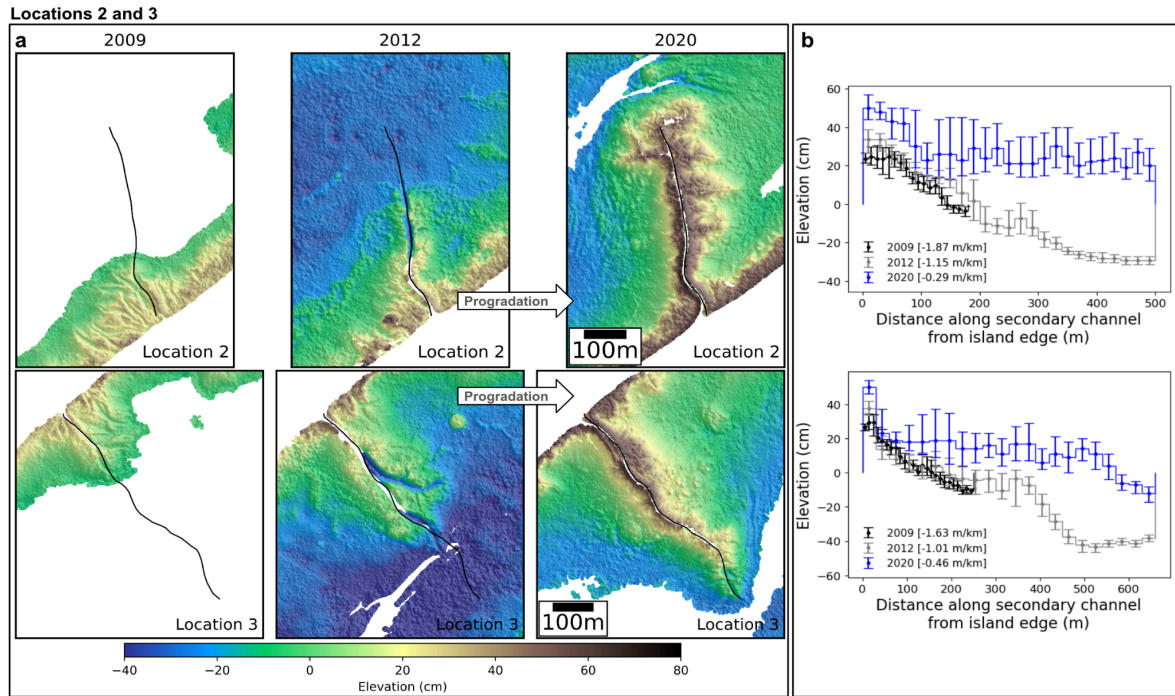
binned with 3m intervals, with negative values representing the left floodplain in the direction of the flowing water, while the profile data are taken across 5-20m of channel extent. The transects are taken from the channels at locations 1, 8, 9, 17, 43, 48, 68, and 4 (annotated in Figure 1). They represent examples of a) a channel that prograded and aggraded, while the channel depths were not captured, but with channel widths,  $W$ : 10m. b) a channel that incised after 2012, with channel depth,  $D$ : 0.45m, and  $W$ : 20m. c) an incising channel filled and its banks losing elevation by 2020, with  $D$ : 0.1m, 0.45m, and  $W$ : 25m, and 35m. d) a plugged channel, with  $D$ : 0.15m, and  $W$ : 30m. e) a channel that incised in by 2012 and aggraded and deepened by 2020, with  $D$ : 0.2m, 0.4m, and  $W$ : 40m, 45m. f) incised channel that got filled with  $D$ : 0.1m, 0.55m, and  $W$ : 10m, 25m. g) an aggrading and deepening channel with  $D$ : 0.2m, 0.35m, and  $W$ : 30m, 20m. h) a location that aggraded 20 cm from 2009 to 2012, before incising a new channel by 2020 and building levees, with  $D$ : 0.35m, and  $W$ : 30m.

### Location 8



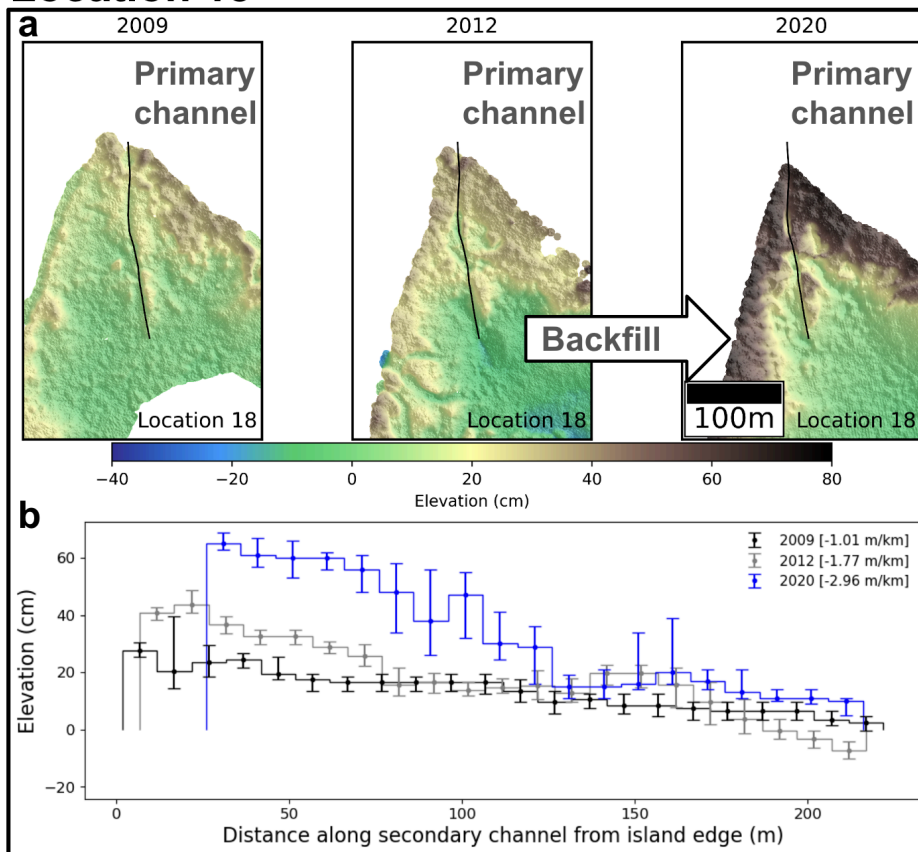
**Figure S9.** Elevation maps and profiles taken at 2009, 2012, and 2020 lidar surveys showing the initiation of the secondary channel at location 8 (Figure S2). The elevation profiles are radially median elevations of all data within the channel lobe, binned every 5% distance along the channel, starting with the island edge.



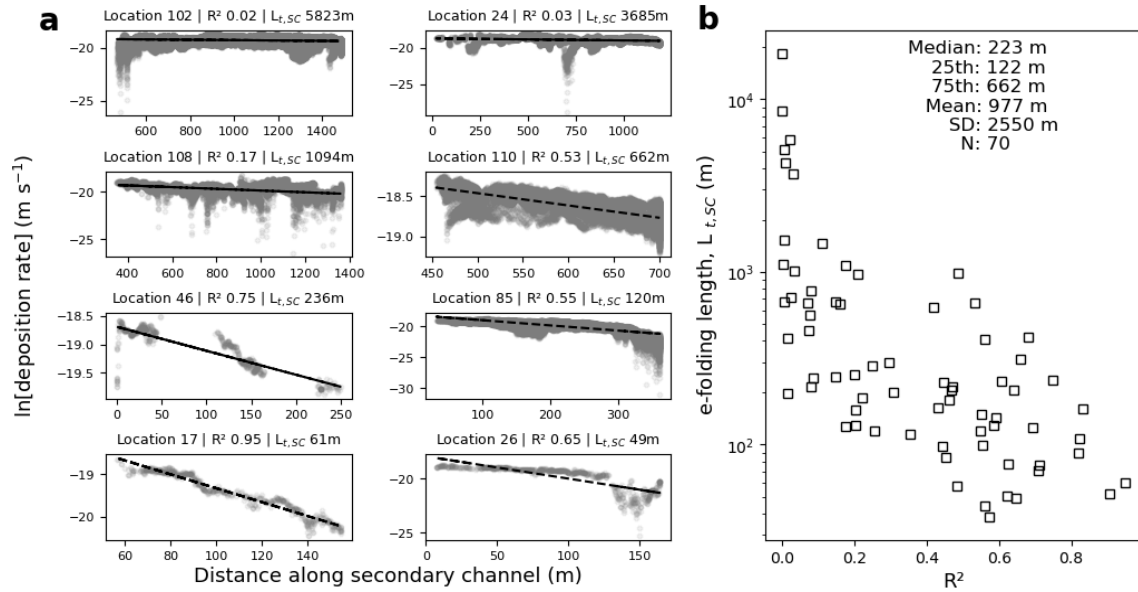


**Figure S10.** Elevation profiles and maps taken at 2009, 2012, and 2020 lidar surveys, showing the progradation of the secondary channel at location 3 (Figure S2). The elevation profiles are median elevations binned every 20m along the channel, starting at the island edge.

## Location 18



**Figure S11.** Elevation maps and profiles taken at 2009, 2012, and 2020 lidar surveys, showing the termination of a small secondary channel at location 17 (Figure S2). The elevation profiles are radial median elevations of all data within the channel lobe, binned at 5% distances along the channel, starting at the island edge.



**Figure S12.** Lidar-based fitting of the exponential decay model (Equation 1). (a) Examples of fitting the deposition rate (y-axis; positive accretion rate values) and distance along the secondary channel from the island edges (x-axis). (b) The fitted e-folding distances,  $L_{t,SC}$  (y-axis) versus the coefficients of determination,  $R^2$  (x-axis).

## CHAPTER 4: A WORKFLOW FOR AUTOMATIC TRACKING OF BARCHAN DUNE MIGRATION, APPLICATION TO QATAR

HUSSAIN ALQATTAN, JEAN-PHILIPPE AVOUAC, PETR POKORNY, CHLOE DAUDON

### Abstract

Barchan morphology and migration, measured from satellite imagery, can provide valuable insights into eolian sand transport and how it varies with environmental conditions. Traditionally, dune displacements have been measured by manually tracking point features. Image correlation techniques are more efficient, particularly for image co-registration, but they have limitations in measuring barchan migration. Texture changes and the scale dependency of bedform migration rates can result in unreliable or meaningless measurements. Recently, deep learning models have been used for automatic barchan segmentation but have rarely been used for tracking. To explore their utility for tracking, we train an instance segmentation model, YOLOv11, on published Martian and Terrestrial datasets of barchan dunes and apply it to dunes in Qatar, where pre-existing manual measurements are available for validation. Once dune boundaries are extracted, we test various automatic methods of measuring displacement. These methods include tracking the moment-based centroid, the median centroid, the farthest interior point, and other features (toe, head, horns). We also use dynamic time warping (DTW), iterative closest point (ICP), and intersection over union (IoU) to measure displacement from dune boundaries. All yielded strong agreement with manually measured displacements and with displacements predicted using sand transport laws and meteorological data. Still, using the entire dune outline (ICP, IoU) reduced the mean absolute error by ~40%. Prompted by the tight packing of dunes in coastal sabkhas relative to inland barchans, we extend the workflow to all barchans in Southern Qatar. Our investigation revealed that coastal barchans have been migrating at rates similar to inland dry regions, suggesting present-day interspacing of coastal dunes is due to relict configuration from more than 1ka BP transgression. Our approach offers a robust solution for automatically detecting, segmenting, and tracking barchans, as well as exploring the effects of boundary conditions on dune fields worldwide.

### 1 Introduction

Barchan dunes are one of the most common dune morphologies on Earth (Goudie, 2020). They can serve a recreational purpose, but they can also overwhelm civil infrastructure and agricultural lands (Boulghobra, 2016; Bruno et al., 2018; Amin & Seif, 2019; Amini et al., 2025). Their simple, often isolated, and crescentic forms, along with

their formation under a uniform wind direction, allow inference of local wind regimes and sand mobility from satellite imagery (Vermeesch & Drake, 2008; Vermeesch & Leprince, 2012). Barchans thus appear as a prime target to study the impact of climate change on aeolian activity, as their dynamics can, in principle, be tracked over large areas and long periods of time using satellite images. In recent decades, dune activation or deactivation has been associated with changes in wind regime, or in bed roughness, e.g., due to vegetation cover alteration and human activities (Wolfe & Hugenholtz, 2009; Baas & Delobel, 2022; Yin et al., 2024; en Kacem et al., 2025; Wang et al., 2025). Relatively high surface moisture content (e.g., in coastal regions) has also been linked with reduced sand transport (Davidson-Arnott et al., 2008). Whether these stabilization mechanisms reduce the overall migration rates of fast-moving barchan dunes remains poorly constrained.

Image correlation is, in principle, a powerful technique to measure migration of bedforms in satellite images and it has been used successfully in a number of studies (Bridges et al., 2012; Hermas et al., 2019). These studies used the Co-registration Optically Simulated Images and Correlation (COSI-Corr) workflow, which optimizes orthorectification and image co-registration and reduces noise in displacement results (Leprince et al., 2007). The technique does not apply well to measure the migration rates of fast-moving barchan dunes of different sizes over long time (Wang et al., 2025). This is because image correlation fails when there is a large object translation or a change in surface texture. Moreover, because the migration of bedforms scales inversely to their size, displacements averaged in the search correlation window might be biased in the presence of dunes of different sizes, or superimposed bedforms, and by the immobile bedrock. For this reason, studies measuring barchan dune migration resort to manually measuring displacement by tracking dune features, e.g., centroid, brinks, horns, toes, across images (Boulghobra, 2016; Michel et al., 2018; Engel et al., 2018; Wahed et al., 2023; Jiang et al., 2024; en Kacem et al., 2025; Dörwald et al., 2025; Cohen-Zada et al., 2026). This approach, as expected, is labor-intensive and, as a result, limits the data size and the scope of the study. In addition, although dunes are assumed to move in a steady state, one may suspect that point measurements are biased by the choice of features.

Although rarely used for tracking dunes, automated methods for dune detection and feature extraction can be extended to large dune fields and have attracted attention in recent decades. These methods have evolved progressively. Threshold-based separation of dunes assumes that dunes have compact, distinct image intensities compared to interdune areas. Because sand often covers both dunes and their interdune areas, this method is often inefficient. Similarly, gradient-based edge detection can lead to imperfect extraction of dune boundaries and crestlines due to spatially variable brightness and contrast, which in turn yield spatially variable gradient magnitudes. In addition, shadows and noise can create false edges. More complex workflows have also

been applied to dune segmentation using computer vision, e.g., object-based image analysis, watershed segmentation, and unsupervised classification. While some studies report successful attempts (Ghadiry et al., 2012; Foroutan & Zimbelman, 2017; Emran et al., 2020; Kazemi Garajeh et al., 2022), the additional step of parameter tuning limits the applicability of these methods to a few locations with almost perfect distinction between dunes and their surroundings. In the last decade, studies resorted to artificial intelligence models, starting from small neural network models to segment dune cover, to large instance segmentation models capable of delineating 1000s of barchan dunes in Earth and other planetary surface (Bandeira et al., 2011; Bandeira et al., 2013; Azzaoui et al., 2016; Azzaoui et al., 2019; Carrera et al., 2019; Rubanenko et al., 2021; Daynac et al., 2024; Cúñez & Franklin, 2024; Scariah et al., 2025; Jiang et al., 2025). Still, there are only a few studies using these models for barchan migration tracking (e.g., Wang et al., 2026).

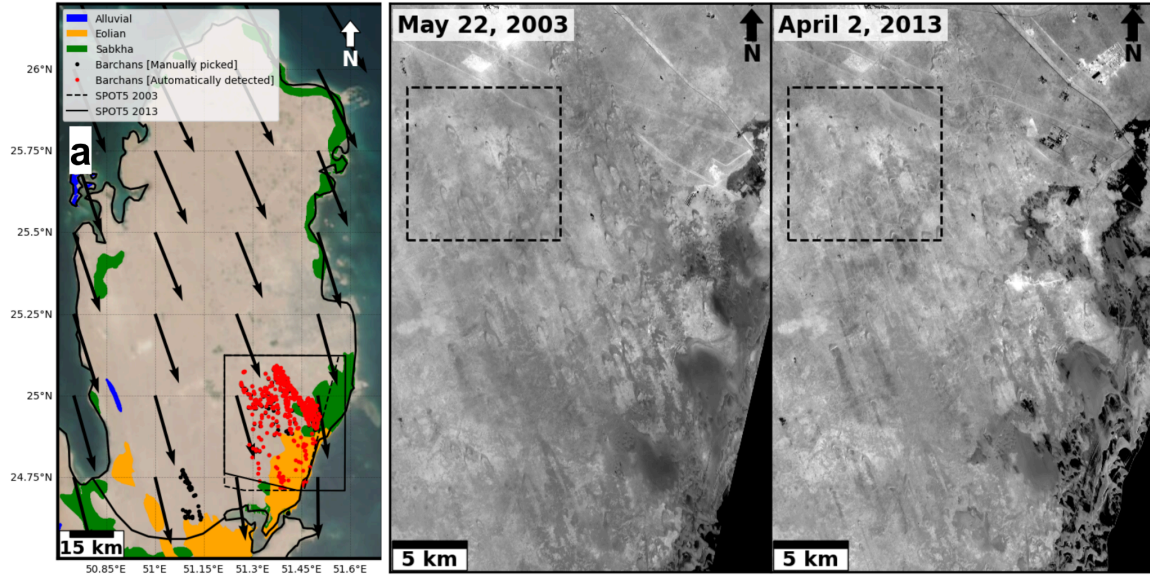
Here, we train an instance segmentation model (YOLOv11) on a compilation of published datasets of barchans from Earth and Mars (Rubanenko et al., 2021; Cúñez & Franklin, 2024), delineate their boundaries, and measure their features. Conventionally, once extracted, the centroids of dune objects (defined as the mean center of area of a 2D object) are calculated for each dune, and the distance between the centroids of each dune pair is calculated as their displacement (e.g., Wang et al., 2026). However, while deep learning models can extract large numbers of dunes, they often produce imperfect object boundaries from satellite images with limited resolution. As such, one could imagine that using individual feature points to represent the dune and measure its displacement can introduce uncertainty. Instead, we explore new methods that have not previously been applied to track barchans. These include both point-based methods (median centroid, farthest interior point, and other dune features) and outline-based methods (dynamic time warping, iterative closest point, and Intersection over Union). The potential strength, or possibly weakness, of outline-based methods is that they use the entire outline of the dune boundary rather than simply the average position to track dunes. For validation, we use a subset of the extracted dune features and migration rates to compare with a manually measured dataset in Qatar (Michel et al., 2018). This ground-truth dataset allowed us to validate our results. Also, we compare sand flux calculated from dune migration to rates predicted from the transport law and local wind data. We then apply our workflow to the dune field in Qatar (Figure 1), which includes isolated, widely spaced barchans inland and more tightly packed barchans in the coastal area. This contrast has been interpreted to reflect either lower migration rates due to a different environment or sand composition near the coast (Embabi & Ashour, 1993; Engel et al., 1998) or a relic configuration due to a past marine transgression (Rivers et al., 2020). We investigate this question using our measurements.

## 2 Study Area

The surface of Qatar is mostly covered with carbonates, while its aeolian, well-sorted, quartz-rich sand cover is confined to the south (Embabi and Ashour, 1992) (Figure 1). Based on migration rates calculated for a few inland barchans and the assumption that their sand source has been cut off, it was estimated that within ~5 kyr from the present, all barchans would be lost into the Arabo-Persian Gulf (Embabi and Ashour, 1992). Compared to mostly isolated barchan dunes inland (Figure S1A), coastal dune morphologies downwind are mostly barchanoid ridges and sand sheets, with a few isolated barchans situated in coastal sabkhas, where interdune spacing is lower than in inland barchans (Figure S1B). Coastal sabkhas extend for kilometers inland in several reaches of the coastal lands, containing evaporite minerals such as gypsum and halite (Embabi and Ashour, 1992; Sadiq & Howari, 2009; Rajendran et al., 2021).

In Qatar, several studies have examined whether dunes in coastal sabkhas (flatlands in arid regions that are rarely inundated and characterized by evaporite content) are more densely packed because they may move more slowly than inland barchans due to higher moisture content (Embabi & Ashour, 1993; Engel et al., 2018). A slowdown is suggested by lower interdune spacing along the coast and by the presence of larger dune morphologies (barchanoid ridges and sand sheets). As an alternative interpretation, the aggregation of coastal dunes, whether barchans or other dune morphologies, might be a remnant configuration of a >1ka highstand period with higher sea levels (~1.6 m) (Rivers et al., 2020) that stabilized and might have reworked the isolated barchan dunes. As such, monitoring the rate of advancement of these barchans is essential and can provide insight into aeolian dynamics under changing environmental conditions.

The climate of Qatar is arid and fairly uniform, with subtle topography. A compilation of ERA5-Reanalysis data shows that the average and standard deviation of temperatures are 28°C and 8 °C, respectively, while the primary wind direction is north-western Shamal, blowing at an average of 4 m/s and a standard deviation of 2 m/s, with a median azimuth of ~170°. To map barchan dunes and their migration rates, we used two panchromatic SPOT5 images from 2003 and 2013 with a resolution of 2.5m (Figure 1). These two images had already been orthorectified and co-registered with a sub-pixel accuracy in a previous study (Michel et al., 2018). A segment of the dune field in the north-west was previously studied, with 62 dunes manually extracted and tracked using the same satellite images used in this study. Manual measurements of migration displacement were taken between points at the dune toe (Michel et al., 2018).



**Figure 1.** Map of Qatar, with the areal coverage of the satellite images, and the locations of dunes studied, in addition to sand cover and sabkhas. (a) Google Earth image of Qatar with the sand cover and sabkhas (GUM v1.0 data; Börker et al., 2018), and both automatically and manually annotated barchan dunes, in addition to the locations of the satellite images. (b and c) Crops of SPOT5 satellite images showing the region of interest and its dunes. In panels b and c, the dashed boxes are the study area with manually sampled dunes (Michel et al., 2018).

### 3 Methods

#### 3.1. Detection, Segmentation, and Prediction

Our goal was to segment barchan dunes with the best possible precision for their use in migration measurements. Here, we use the large version of the instance segmentation model, You Only Look Once (YOLOv11) (Jocher, 2020), trained on previously labeled data for segmenting barchan dunes on Mars and several regions on Earth with similar barchan morphologies (Rubanenko et al., 2021; Cúñez & Franklin, 2024). To better align with our goal, we removed any images that were not map views of barchans, were not based on satellite imagery, had low resolution, or lacked the distinct crescentic barchan shape. From a total of 1009 images, we cropped them to 1024X1024 and divided the dataset into 705, 201, and 103 for training, validation, and testing, respectively. To improve model performance, we also added a few crops from the study area after labeling them with an open-source annotation tool (Bhattiprolu, 2024) that uses the high-precision segmentation model “SegmentAnything” (Kirillov et al., 2023). Furthermore, augmentation steps were added to vary the rotation, brightness, contrast, downscaling, and blurring of the training images, among other modifications, using the

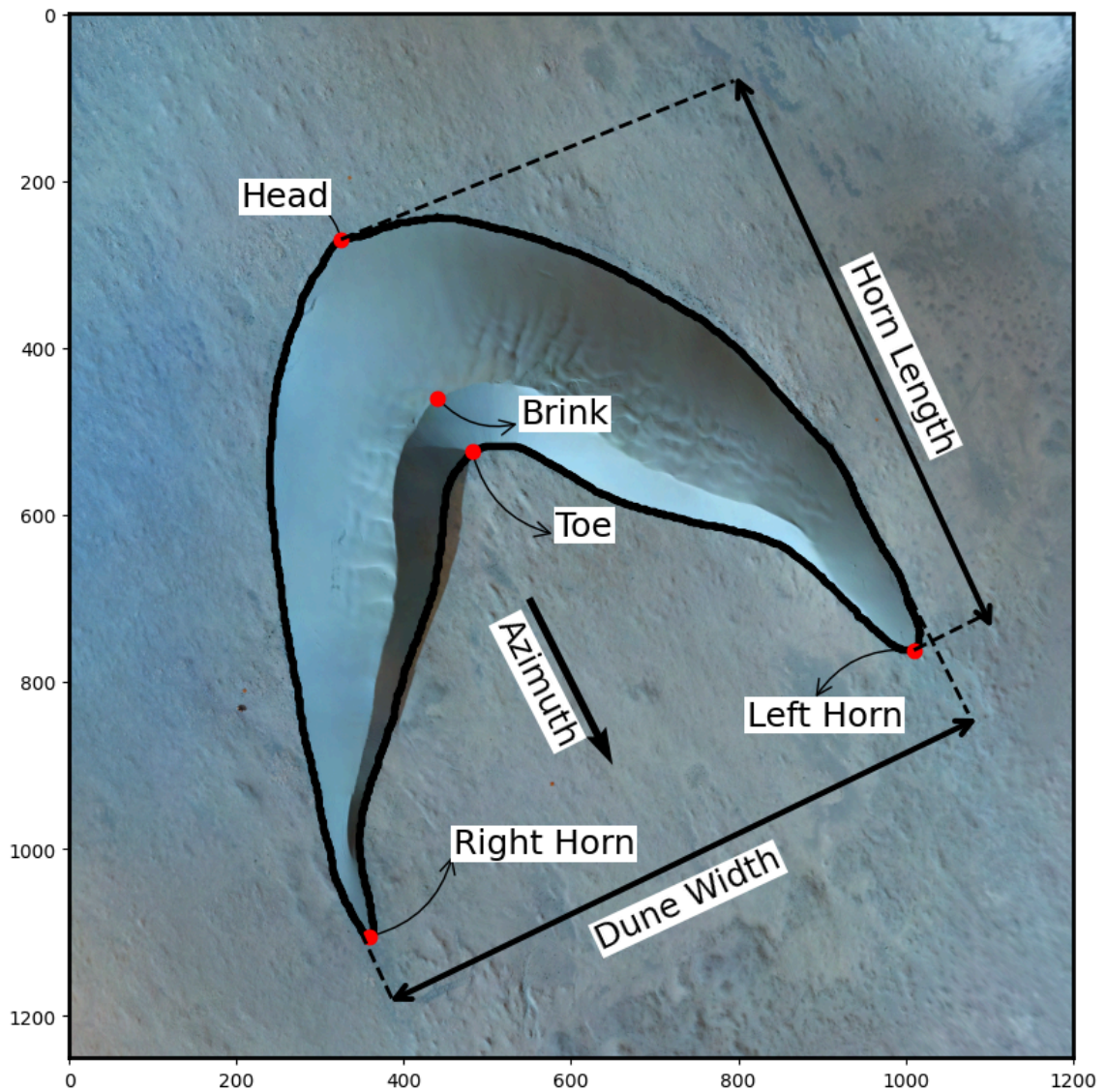


“Albumenations” library (Buslaev et al., 2020). In the training YOLO package from Ultralytics, the optimization algorithm was set to automatic, starting with the “Adam” optimizer and switching to SGD for better fine-tuning. The probability of these augmentations was set to 20%. The training was retrained multiple times for a total of more than 3700 epochs, until no further improvement was observed.

Because barchan dunes in the study area had variable sizes, and the satellite images covered a large area, we used a Slicing Aided Hyper Inference (SAHI) library designed to break large images into tiles and vary the resolution of each crop to optimize model inference of small objects (Akyon et al., 2021, 2022). Still, we ended up with several false positives, as observed also by Rubanenko et al. (2021). We tried several methods to automatically exclude them. This included rescaling the dunes, measuring L1 and L2 distances between their vertices, and comparing Hu moments with an ideal mean shape. However, some detected barchans had ideal shapes, while others did not. In particular, dunes that were flagged as outliers were dunes that had elongated horns or small dunes with coarse and low-resolution features. We applied a defect ratio metric, defined as the ratio between the largest convexity-defect lengths (Rubanenko et al., 2021; Jiang et al., 2025), which removed some true positives.

### *3.2. Barchan properties*

Once dunes were automatically detected and delineated, and manually verified, several properties were extracted from their contours (Figure 2). The position of the slipface toe was extracted as the point with the largest convexity-defect length, and the position of the horns was extracted from the associated convex hull edge, similar to (Rubanenko et al., 2021). The position of the head is also extracted as the farthest point from the two horns. The horn lengths were extracted as the projected length between the horns and head parallel to the toe-head line (Figure 2). Similarly, the dune width is extracted as the distance between the two horns projected on the line orthogonal to the toe-head. Alternatively, we extracted additional measurements of dune widths to test which better matched the ground truth. These include the square root of the dune area, the square root of the best-fit rectangle area, and its shortest rectangle side. The bivector of the two vectors from the head to the two horns is used to calculate the internal azimuth of each dune.



**Figure 2.** A close-up of a barchan showing its geometrical elements (boundary, length, width, horns, azimuth). The slipface length is the distance between the brink and toe.

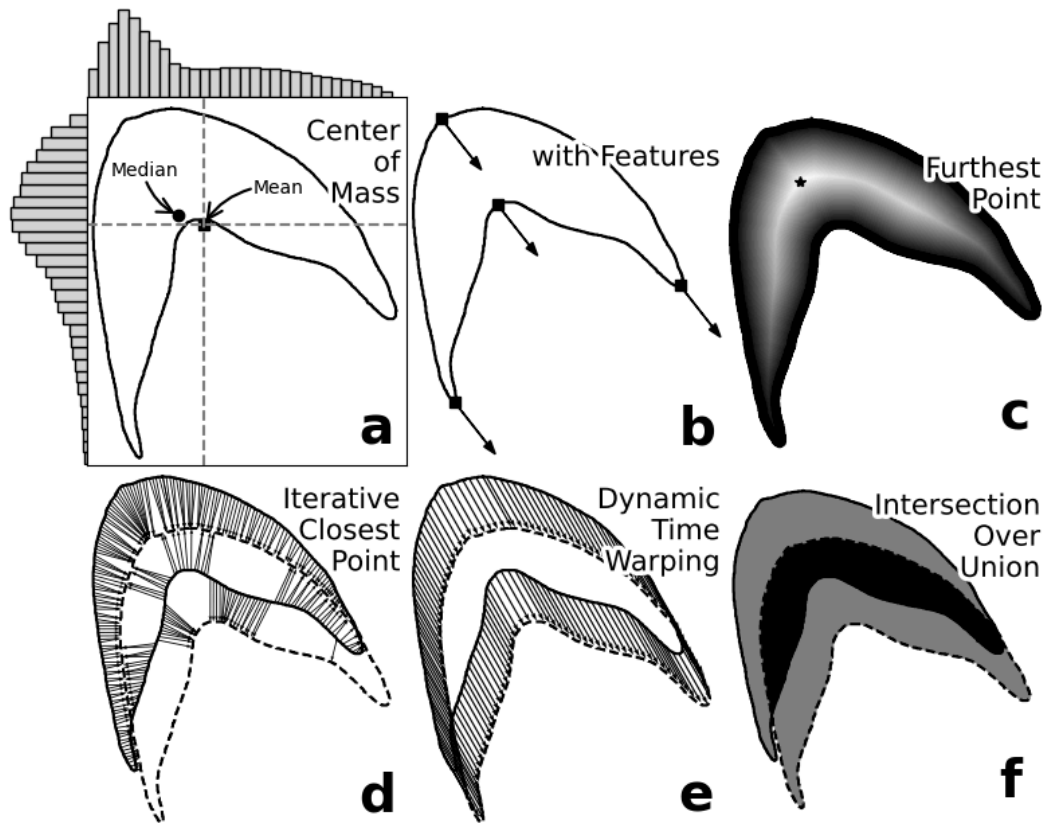
### 3.3. Tracking

The conventional method for tracking fast-moving dunes is to manually match dune feature points across images. To improve efficiency, the common automatic method is using the centroid of each dune pair (Figure 3A), followed by measuring their Euclidean distance, or their features (heads, toes, and horns) (Wang et al., 2026). Suspecting that the centroid positions can be affected by imperfect dune contours, we experimented with additional methods not usually used to track barchan dunes (Figure 3). Similar to

using the mean position along each axis (the centroid), we extracted the median position along each axis (Figure 3A). Using the extracted points from the contour shape, we measured displacement as the average Euclidean distance to the toe, head, and two horns in the dune candidate. In addition, we experimented with a new feature point defined as the farthest interior point that maximizes the total distance from the contour vertices (Figure 3C). To enhance the accuracy of finding this point, we refine each dune by adding more points along its edges.

Using additional information from the dune contour, we applied a method similar to the “Iterative-Closest-Point” (ICP) (Besl and McKay, 1992) to find the optimal displacement vector that minimizes the average Euclidean distance between the boundary points of two corresponding dunes (Figure 3D). This method allows comparison of point clouds (Teza et al, 2007). Next, we used Dynamic Time Warping (DTW) to calculate the average displacement vector (Figure 3E). This method has been used to track fluvial and deltaic channels (Sylvester et al., 2019; Wang et al., 2025). Similarly, we first center the dune pair at its centroid, then convert the 2D dune shape into its radial profile. From there, we apply dynamic time warping to calculate for each point its matching point in the candidate dune. The displacements between the matched points are then calculated. Another method of measuring displacement is by translating one dune until the intersection-over-union (IoU) is maximized. Next, we use the optimal solution as the displacement vector between two dunes (Figure 3F).

We also experimented with two additional methods using both the dune contours and the dune intensity information. In one method, we used the Python library OpenCV (Bradski, 2000), which is termed “template matching”. In this method, the masked dune crop is translated across the 2013 satellite image, and the Pearson correlation coefficient is calculated at each position between the intensity values of the two images. The distance between the initial dune location and the pixel with the maximum coefficient magnitude is used as the displacement vector. We used a masked version of the dune to avoid interference from the intensity information of regions surrounding the dunes. We found that for many dunes, multiple peaks in the correlation map suggest multiple candidate dunes, sometimes with even higher correlation than the “true” candidate. For that, we only consider peaks that were at the candidate dunes that were already paired by the next step. For completeness, we also used the phase correlation method in another Python library (skimage; van der Walt et al., 2014), which uses the Fourier transform to correlate dunes based on their intensities. We found that a valid correlation was only possible when the dunes and their candidates were masked using their contours. As such, it may be that the overlap between the masks, rather than the intensity values, is being correlated.



**Figure 3.** Several methods of calculating displacements using “before” and “after” dune boundaries, including: (a) extracting the mean, also called the centroid, and the median centroid from the dune histogram along its x- and y-axis. (b) feature tracking of the toe, head, and two horns. (c) Extracting the farthest interior point that maximizes the total Euclidean distance from the dune vertices. (d) Iterative closest point method, translating the dune until a minimum total distance to the candidate dune is achieved. (e) Dynamic time warping, with points matched by centering the two dunes at their mean centroid, calculating their radial profiles, then applying dynamic time warping on the profiles. (f) “Intersection-over-Union” where the dune contour is translated until a maximum intersection (black shading) over union (black and gray shading) is reached.

### 3.4. Candidate pairing

Once dunes are extracted from a time series of satellite images, pairing them is a non-trivial task. Using the closest dune can yield invalid candidates, since dunes of similar size can aggregate together. To that end, we apply several conditions to identify the best dune candidate. First, dune candidates that are moved more than 100 m per observation year were excluded. Next, the area ratio between all dunes is calculated as the minimum area divided by the maximum area of each dune pair, and any pair that

has less than 0.3 is excluded. Next, the displacement vector between all remaining possible dune pairs is calculated to measure the maximum IoU percentage and the migration azimuths. Using the area ratios, the maximum IoU, and the difference between the internal and migration azimuths, a cost matrix is calculated. Finally, a function from the SciPy Python library is used to solve the linear sum assignment problem. This function is meant to find for each dune a candidate dune that minimizes the total cost, with no duplicate candidates for any dune. Still, some dune pairings were manually corrected due to imperfect dune delineations that altered dune areas or led to incorrect azimuth calculations.

### *3.5. Metrological and satellite-derived datasets*

To investigate whether local conditions affect the shape and migration rate of dunes, we extracted several environmental indicators. We extracted meteorological variables from ERA5 Reanalysis data (Hersbach et al., 2020) between 2003 and 2013, including total precipitation, temperature, and the two components of wind velocity. We also use in situ wind data in Qatar within the dune field (Michel et al., 2018). Both in situ minute-level and ERA5 hourly reanalysis wind data were used to calculate sand flux and migration rates predicted using the transport law of Kok et al. (2012), which was found to best fit the measurements from Qatar (Daudon et al., 2024). Although we attempted to calculate the dune brink height, not all measurements were accurate or survived the filtering stage. Instead, we opted to use an empirical fit ( $\text{width} / 12.45$ ) (Jiang et al., 2024), which we found to fairly align with a trial method we experimented with of automatically measuring slipface lengths (i.e., distance from brink to toe) (Text S1; Figure S3A). Another required parameter for the migration rate prediction model was the stoss length (Figure 2), for which we also applied an empirical model ( $4.6 \times \text{height} + 18.5$ ) (Sauermann et al., 2000) that fairly aligned with our roughly estimated lengths (Text S1; Figure S3B). This allowed us to compare measured migration rates with calculated rates and to determine which method aligns better with model predictions.

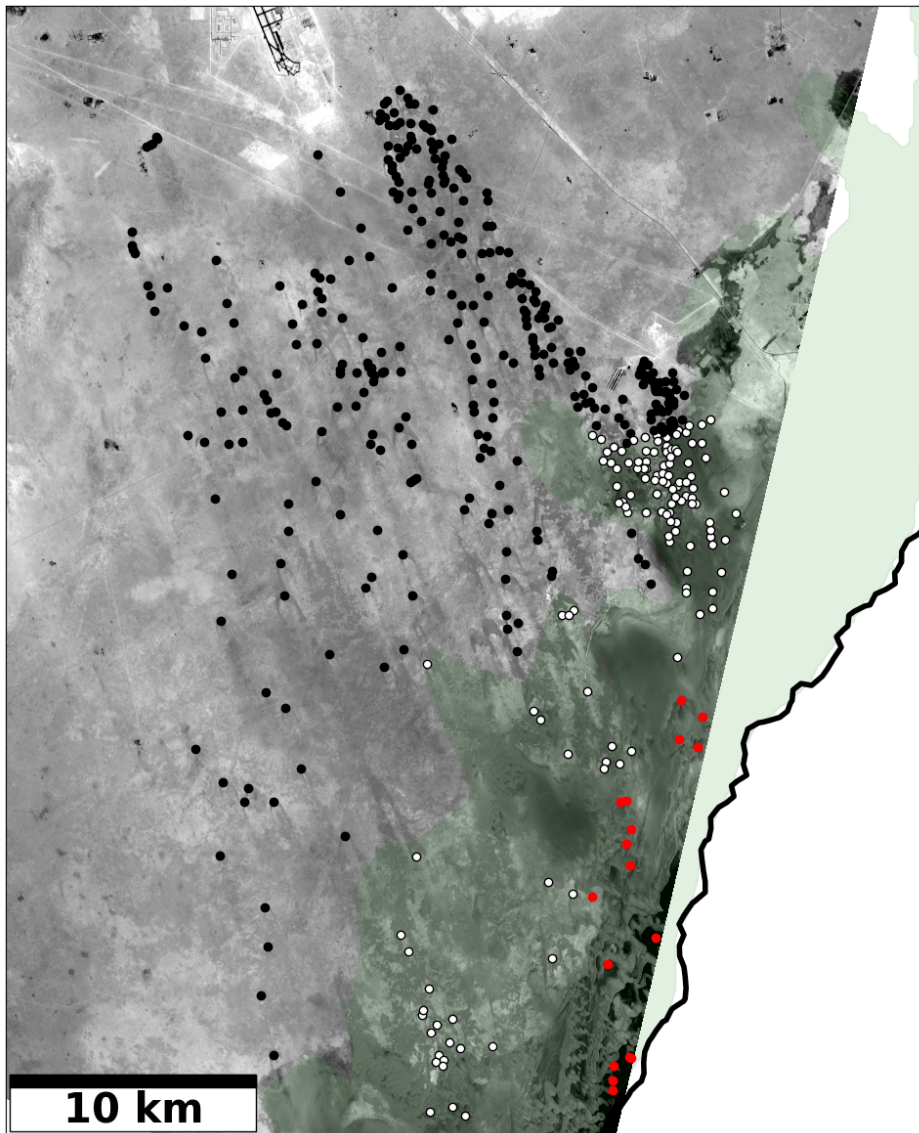
To approximate land conditions (inundation, moisture, and salinity), we first extracted 136 Landsat images at 30m spatial resolution and 62 Sentinel images at 10m spatial resolution, collected between 2003 and 2020. All Landsat and Sentinel images were acquired using the Google Earth Engine API (Gorelick et al., 2017). Next, we calculated three indicators for each satellite. One, to gauge inundation, we calculated both the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI). We generated a water mask by multiplying the two. Then, we aggregated them and divided by the total number of images, generating a map of the probability of water non-exceedance. Second, assuming coastal lands that are occasionally inundated would be more saline and less arid, we extracted the Vegetation Soil Salinity Index (VSSI) and the Normalized Multi-band Drought Index (NMDI). The VSSI index is often used to indicate salinity levels in coastal areas, including in Sabkhas (Nguyen et al., 2020; Amin,

2021; Hassan et al., 2021), and was calculated from the green, red, and near-infrared (NIR) bands (equation 1). Third, the NMDI index was calculated to gauge drought (Wang & Qu, 2007) using near-infrared and short-wave infrared bands (equation 2). Although VSSI and NMDI generally aligned with the expected locations of coastal sabkhas, we instead used a land mask (GUM v1.0 data; Borker et al., 2018) and classified dunes within this mask as sabkha dunes.

$$\text{VSSI} = 2 \times \text{Green} - 5 \times (\text{Red} + \text{NIR}) \quad (\text{equation 1})$$

$$\text{NMDI} = (\text{NIR} - (\text{SWIR1} - \text{SWIR2})) / (\text{NIR} + (\text{SWIR1} - \text{SWIR2})) \quad (\text{equation 2})$$

We analyzed whether barchan dunes in Qatar are stabilized at the coast by inundation, moisture, proximity to a sand source, or their unique mineralogy. To capture this effect, we used two approaches to divide the dunes. First, we divided the barchans into inland and coastal (within 4km of the coast). In the second approach, we divided them into two groups based on whether they lie within or outside the sabkha. To compare the two populations, we used three metrics. The first is the percentage decrease in the IoU-based migration rate relative to the rate predicted by an empirical model fitted to the inland barchans (Michel et al., 2018). The second metric was the residual, defined as the difference between the migration rate predicted from in situ wind data (Daudon et al., 2024) and the IoU-based measured rate. For the third metric, we used the sand mass flux per unit width, calculated as the IoU-based migration rate multiplied by the height, the solid fraction (40% porosity), and the sand density (2630 kg/m<sup>3</sup>). Next, using analysis of variance (ANOVA), we tested whether coastal and sabkha barchans differ from inland barchans (Figure 4).



**Figure 4.** Classification of barchans as inland (black), sabkha (white and red), and within 4km from the coast (red). Sabkha extent is shaded in light green. The background is the SPOT5 image acquired in 2003. Similar maps are displayed with the background set as the topography (Figure S4), median VSSI (Figure S5), and median NMDI (Figure S6).

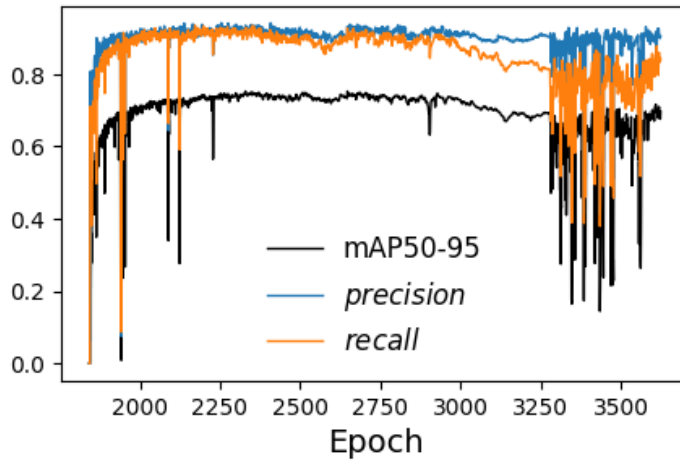
## 4 Results

### 4.1. Model performance

Testing the model's performance yielded satisfactory results (Figure 5). In such a model, performance is evaluated by measuring the intersection-over-union (IoU) between model predictions and the ground-truth dataset for both bounding boxes and masks.



Measurements of IoU above a certain threshold (e.g., 0.5 or 0.95) are defined as true positives (TP). Using these measurements, three metrics are often measured. Recall is defined as the ratio of true positives (TP) to the sum of true positives (TP) and false negatives (FN). Precision is defined as true positives (TP) relative to the sum of true and false positives (TP and FP). A third cumulative metric is the mean Average Precision (mAP), which is the area under the precision-recall curve. Based on bounding box predictions in the test dataset, recall, precision, and  $mAP_{50}$  are about 0.86, 0.93, and 0.93, respectively. The mask prediction performed similarly with recall, precision, and  $mAP_{50}$  are about 0.87, 0.93, and 0.93, respectively. In comparison, a stricter metric that combines several thresholds ( $mAP_{50-95}$ ) reached 0.77 for bounding boxes and 0.72 for masks. These metrics are higher than those reported in other models for the same instance segmentation task (Rubanenko et al., 2021; Wang et al., 2026) and are similar to those reported by others (Cúñez & Franklin, 2024).



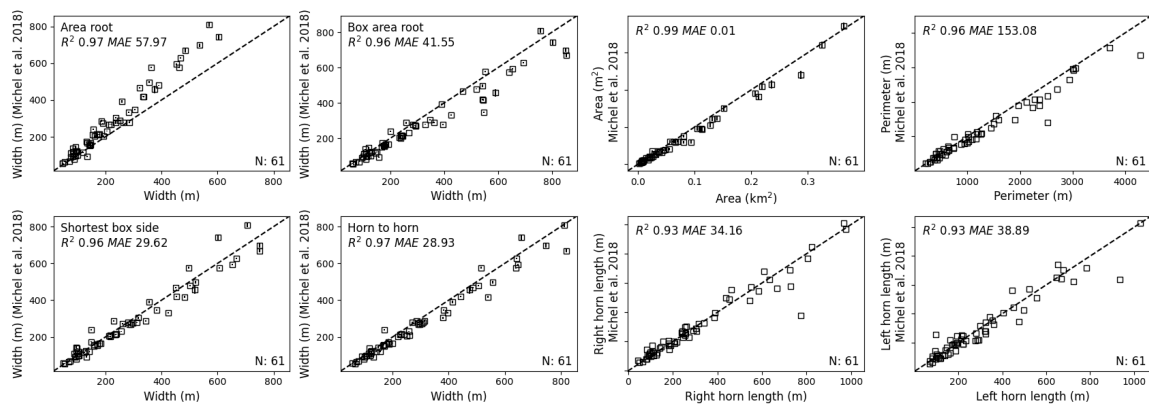
**Figure 5.** A segment of the model training performance, showing the  $mAP_{50-95}$  metric, precision, and recall, computed by comparing predicted masks with ground truth in the training dataset.

#### 4.2. Validation of dune properties and migration measurements

Using the best-performing model iteration and the SAHI workflow, we extracted almost all isolated barchan dunes from the two SPOT5 images. While the migration displacements were measured from two SPOT5 satellite images, the manually measured geometric features of the dunes were measured from a different image (DigitalGlobe satellite) with higher resolution ( $\sim 1.5m$ ) and a later date, February 2, 2015 (Michel et al., 2018). Not all dunes were detected because they were too small or their shapes did not match the conventional crescentic barchan shape. Still, 57 dunes were detected among the 62 manually sampled dunes in the 2003 image, and 61 dunes were found in the 2013 image. To compare with the more recent image, we matched the ground-truth

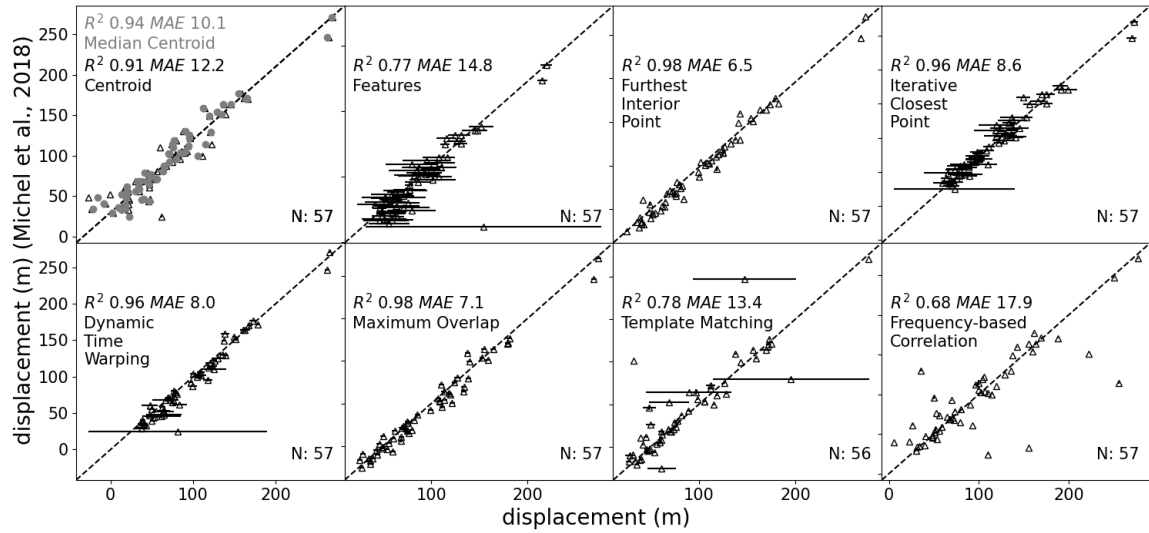


geometric dune features to the 2013 image. Out of the four methods of calculating dune widths, the best match to ground-truth was the method using the distance between the two horn sides orthogonal to the head-slipface axis (Figure 6). Still, the widths derived from the shortest sides of the best-fitting boxes were similar (Figure 6). The other geometric features (area, perimeter, and the lengths of the two horns) also have low mean absolute errors and high coefficients of determination relative to ground-truth data (Figure 6). The residuals were either due to imprecise delineation of the dunes, inherited error from resolution disparity, or could indicate that the dunes have been getting smaller between 2013 and 2015. No similar trend was found between 2003 and 2013.

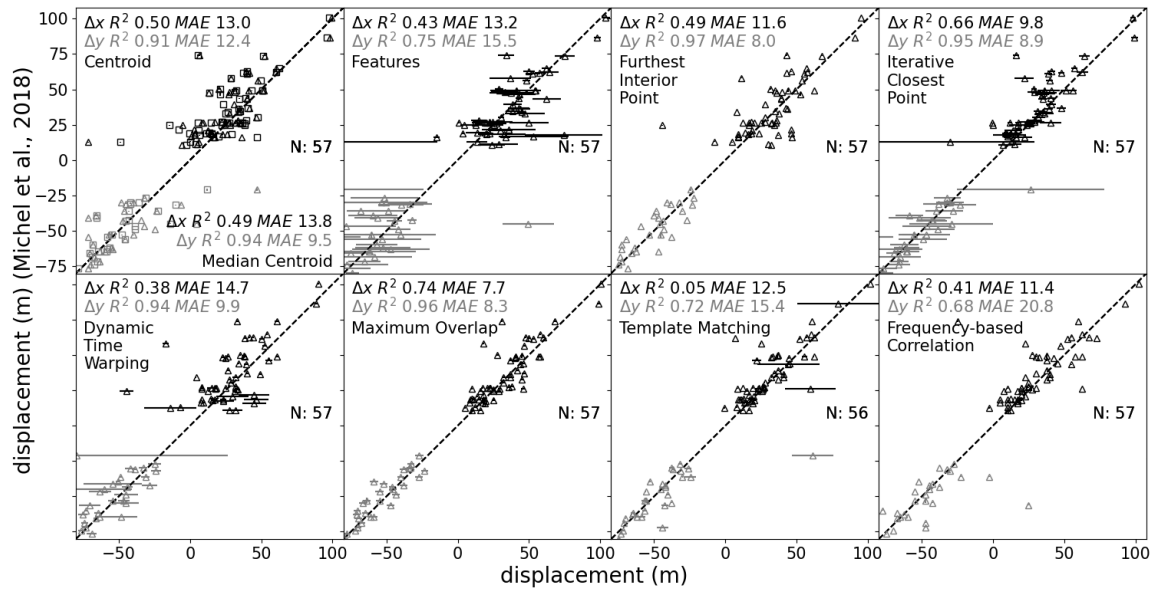


**Figure 6.** Comparison of measured geometrical dune parameters to groundtruth parameters measured manually (Michel et al., 2018).

Comparing the various tracking methods confirmed our expectations. Methods using the outlines of dunes are more accurate (MAE 7.1-8.6) than using centroids (MAE 10.1-12.2) (Figure 7). Even median centroids performed better than the conventional moment-based centroids. Surprisingly, while using other feature points yielded higher error residuals than centroids (MAE 14.8), using the furthest interior points yielded better results (MAE 6.5), comparable to IoU-based displacements (MAE 7.1). However, when investigating the two displacement components, IoU-based tracking performed best (Figure 8). On the other hand, methods that used image intensity values for matching performed relatively poorly (Figure 7; Figure 8); this performance was expected because dune morphology and image-texture changes reduce, and even invalidate, tracking based on image correlation.



**Figure 7.** Comparison of measured displacement magnitudes using various tracking methods with ground-truth displacement measured manually (Michel et al., 2018).

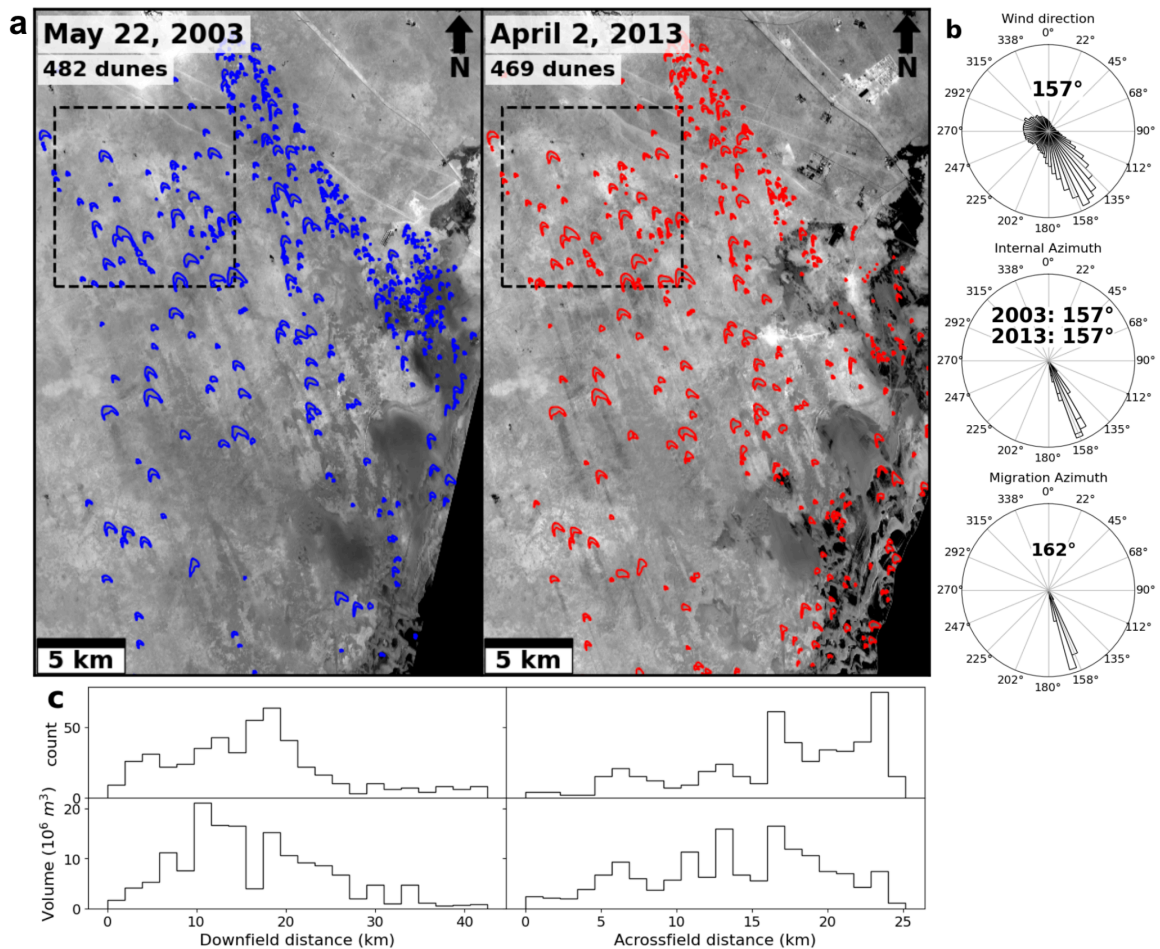


**Figure 8.** Comparison of measured displacement components using various tracking methods with ground-truth displacement components measured manually (Michel et al., 2018). In each panel, both the x-component (East) displacement (black) and y-component (North) displacement (gray) are displayed.

#### 4.3. Statistics and scaling of barchans in Qatar

A total of 482 and 469 dunes were sampled in the two SPOT5 images, 2003 and 2013, respectively (Figure 9A). Their average width is approximately 227m, ranging from ~8m

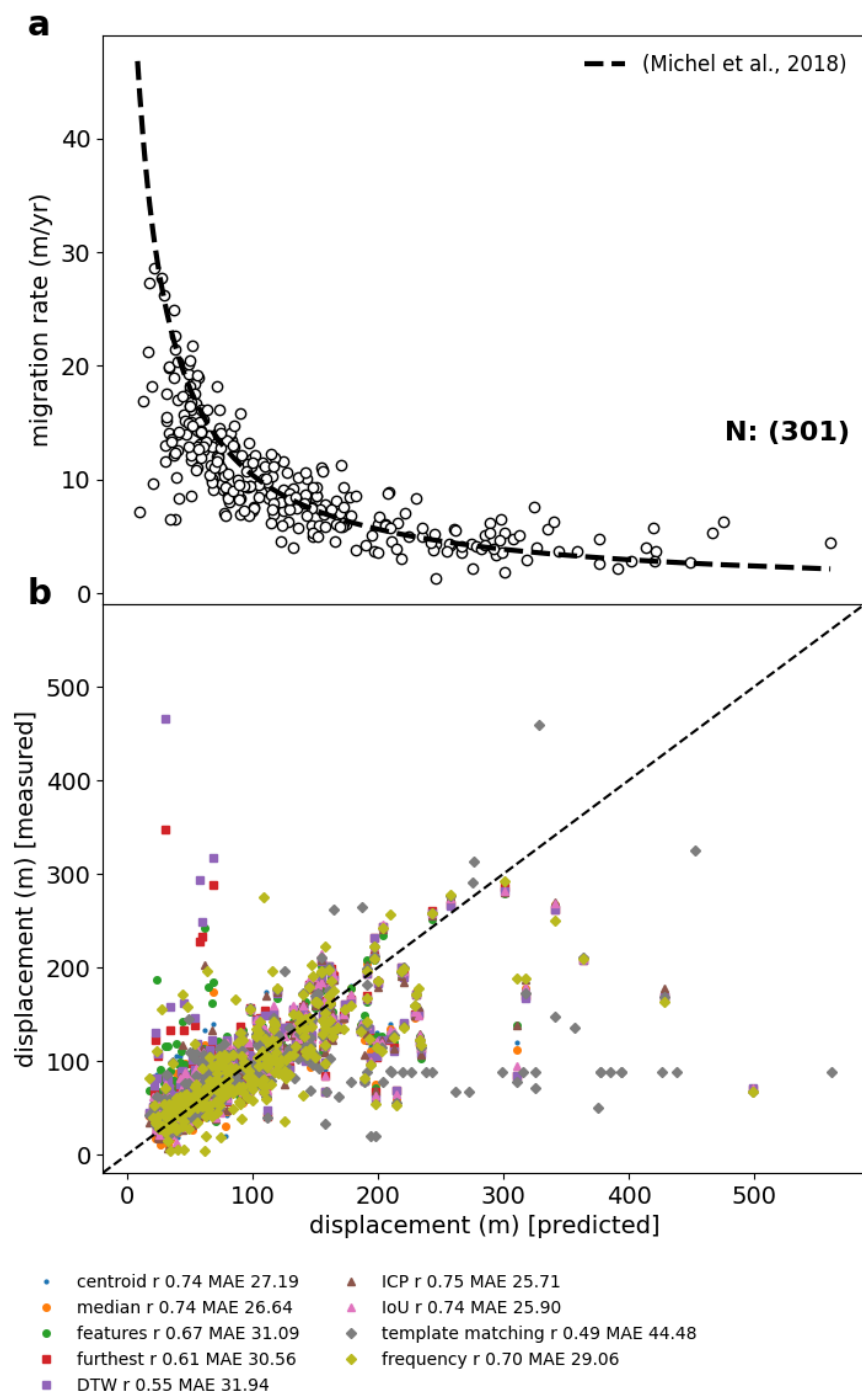
to ~1260m. The average migration and internal azimuths of 162° and 157°, respectively, matched the wind azimuth, 157° (Figure 9B). Most of the dunes are in the east and upwind edge of the field (Figure 9C). When volume is adjusted for, the dunes are distributed more evenly laterally, but they still mostly occupy the upwind segment of the dune field. There is a positive correlation between interdune spacing and size (Pearson correlation coefficient,  $r = 0.36$ ). In contrast, interdune spacing showed a higher correlation with lateral distance ( $r = -0.70$ ). Mean interdune spacing is ~1300 m with a standard deviation of ~1000 m, and a range of ~100- 6000 m, defined as the square root of the trapezoidal area around each dune (Durán et al., 2008). These interdune spacings were calculated between barchans, excluding sand sheets and more complex dune morphologies at the coast. 99 of the dunes had right-side horns extended, while 81 dunes had larger right-side horns (Figure S7). We also counted 63 barchans without well-developed slipfaces, and 21 dunes that evolved into barchanoids (Figure S7).



**Figure 9.** Spatial distribution of the barchan dunes. (a) the two satellite images with the dune contours displayed. (b) radial histograms of the ERA5-Reanalysis wind direction

(2003-2013) at the dune field location, internal azimuths (bisector vector between head-horns vectors) of dunes in 2003 and 2013, and their migration azimuths, with mean azimuths (bold). (c) histograms of the dunes as a function of their downfield and acrossfield distances (x-axes), and their count, and volume (y-axes). In panel a, the dashed boxes are the study area with manually sampled measurements used as ground-truth (Michel et al., 2018)

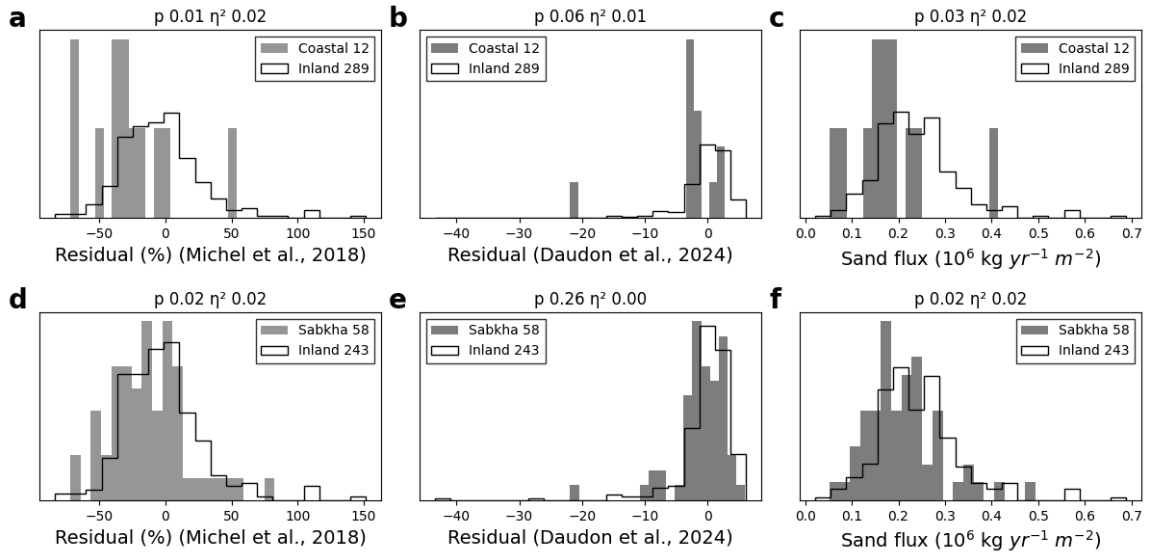
Out of all dunes, a total of 301 dunes were paired. The average IoU-based migration rate is approximately 10.1m/yr, with a maximum of 28.5m/yr and a minimum of 1.3m/yr (Figure 10A). We found that rates derived from in situ minute-scale wind-velocity data aligned more closely with our measured migration displacements. Out of the various methods, ICP-based rates performed the best ( $r$  0.75 and MAE 25.71; Figure 10B), followed by the IoU-based rates ( $r$  0.74 and MAE 25.90). Both the mean and median centroid-based displacements also performed relatively well (MAE 26.64-27.19), better than the farthest interior point (MAE 30.56), better than using dune features (MAE 31.09), better than DTW, which uses all points along dune contours (MAE 31.94), and better than methods that used image intensity, i.e., template matching and frequency (MAE 29.06-44.48).



**Figure 10.** Measured migration displacements. (a) IoU-based migration versus width, and (b) all measured migration displacements versus displacements predicted using the Kok transport law and in-situ wind velocity data.

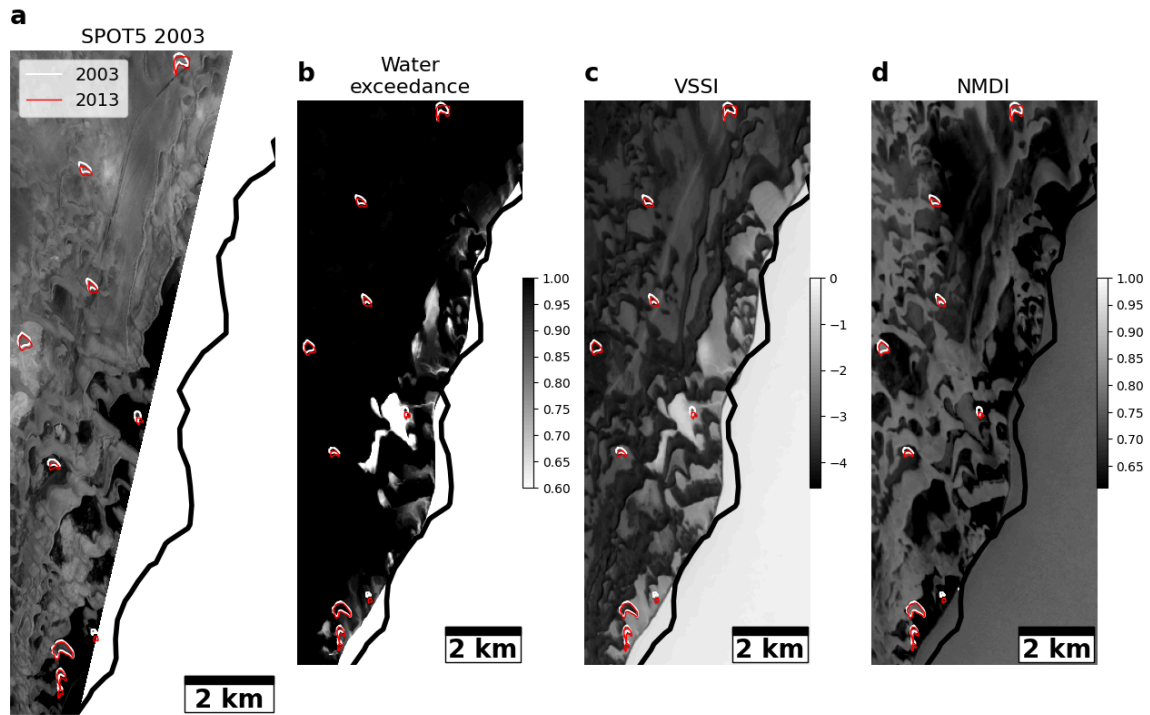
#### 4.4. Do barchan migration rates change near the coast?

Dune tracking reveals that coastal barchans and barchans within the sabkhas migrated during 2003-2013 at a rate similar to that of dry inland barchans (Figure 11). Satellite-derived indicators at these sabkhas suggest that areas within 2km from the shoreline are more inundated (Figure 11B). It follows that coastal areas experience less vegetation stress than inland regions, as indicated by median VSSI values (Figure 12C; Figure S5). However, median NMDI values indicate that dunes are generally drier than interdune areas, whether inland or at the coast (Figure 12D; Figure S6). While inundation frequency is higher at coastal regions, and the topography is lower toward the gulf (Figure S4), the difference in migration rates between sabkha/coastal barchans and inland barchans is not significant. Although the p-value for the residual percentage was below 0.05, indicating rejection of the null hypothesis, the distinction explained less than 3% of the variance (Figure 11). Moreover, we have not found any significant correlation between the residuals and spatial metrics (distance from the coast, acrossfield distance, and downfield distance), nor with the satellite-derived indicators, or the metrological parameters.



**Figure 11.** Comparisons between inland and coastal migration rate residuals and sand flux, within 4km, barchans (a, b, c), and inland and sabkha barchans (d, e, f). Both the p-value and the explained variance ratio are displayed for all panels. (a & d) The residual percentage is defined as the percentage decrease of the IoU-based migration rate from the rate predicted by the empirical model fitted on inland dunes. (b & e) Residual from

differencing the IoU-based migration rate from rates predicted with the transport law of Kok et al (2012). (c & f) sand flux, or mass flux per unit width. The numbers displayed in the legends are the number of barchans in each category, out of a total of 301 dune pairs.



**Figure 12.** Coastal barchan migration with satellite-derived indicators. (a) SPOT5 satellite image, acquired in 2003. (b) Water exceedance map. (c) VSSI. (d) NMDI. All maps show the segmented dunes in 2003 and 2013, showing their displacement.

## 5 Discussion

Our study examines the obstacles and potential of automatically segmenting and tracking barchans. Pairing dunes, particularly with larger time spans and aggregated populations of dunes, is non-trivial. First, using an automated workflow to pair dunes based solely on proximity, area, azimuth, and overlap yielded strong results. We avoided incorporating information from image intensity and texture into the pairing workflow, as our template-matching-based displacement calculations have yielded fair to poor results. In the future, we recommend using neural network encoders to match and pair dunes based on their image intensities, which we found showed promising results for matching similar dunes (Figure S7). Second, even with a large model, inferences of barchans yielded several false-positive identifications, which increased with smaller dunes. Future work would benefit from improved automated workflows to remove

“false” dunes and reduce uncertainty in derived measurements. Third, imperfect delineation of dunes can reduce the accuracy of property and displacement measurements. Our proposed workflow has reduced uncertainty in displacement measurements by incorporating the entire dune outline rather than a single centroid point or a few features. In addition to extracting morphometric parameters and displacements, automatically segmenting dunes can improve image co-registration prior to displacement measurements (Baird et al., 2019).

Our dataset is the most extensive in measuring migration rates and dune properties in Qatar (Embabi and Ashour, 1992; Michel et al., 2018; Engel et al., 2018). Larger dune sizes could have resulted from dune merging. As such, the correlation, although faint, that we found between interdune spacing and barchan sizes aligns with a widely recognized pattern in dune fields (Durán et al., 2008; Jiang et al., 2024). Such an arrangement supports the idea that dune interactions inversely correlate with interdune spacing (Day & Kocurek, 2018). This suggests that coastal dunes may result from inland desert dunes accumulating along the coast as they migrate, with their migration path ending at the Gulf. This is different from typical coastal dunes that form when sand from the beach is delivered by the ocean (e.g., Brazil; Hesp & Walker, 2022). This scenario can also be encountered in other hyper-arid deserts (e.g., Namibia). Dune volume and count distribution reveal that the downwind segment of the dune field is depleted of sand (Figure 9), which could have leaked into the coastal dunes; since the barchans in Qatar are disconnected from their sand source, they are most likely continuously losing sand that has accumulated in other dune morphologies near the coast (Michel et al., 2018). Higher sand availability at the coast should have exchanged sand with the coastal barchans, reducing their migration rates. However, no distinction in migration rates was observed.

The placement of these dunes at the sabkha site along the southern coast of Qatar suggests that another mechanism is at play. Transgressive sea levels have submerged several kilometers inland since the mid-Holocene, potentially stabilizing the dunes by freezing them in place and reworking them, altering their morphology. Once the water levels that submerged aeolian sand dunes were lowered, relict sandy deposits and sabkha deposits were exposed. Since then, dunes have been released and reactivated, with migration rates similar to those of inland dunes, as revealed by our measurements. Moreover, the dunes at the coast seem to increase their interdune spacing as they mature closer to the coast, as previously observed in nature (Ewing et al., 2006) and in numerical simulations (Durán et al., 2011).

There is a possibility that changes in coastal barchan migration rates are acting on scales beyond the ~10-year study period. It has been shown previously that dune migration in Qatar varied from 2006 to 2015, possibly due to increased sand mining or changes in the wind regime (Engel et al., 2018). If inundation events are sporadic, their effects might be



limited to short time periods. On the other hand, if the proximity to sand sources at the coast increases the volume of barchans, the slowdown of their migration rates might be delayed.

## 6 Conclusion

The workflow described in this study offers a robust solution for automatically detecting, segmenting, and tracking barchans, and for exploring the effects of boundary conditions on dune fields worldwide. The approach we developed for barchan dunes in Qatar can be transferred to any dune field with barchans, including much larger barchan dune fields in Taklamakan in Northern China, in Rub' al-Khali in East-South Saudi Arabia, in the West of Namibia, and in Western Sahara in South Morocco, among others, where barchans are abundant (Goudie, 2020).

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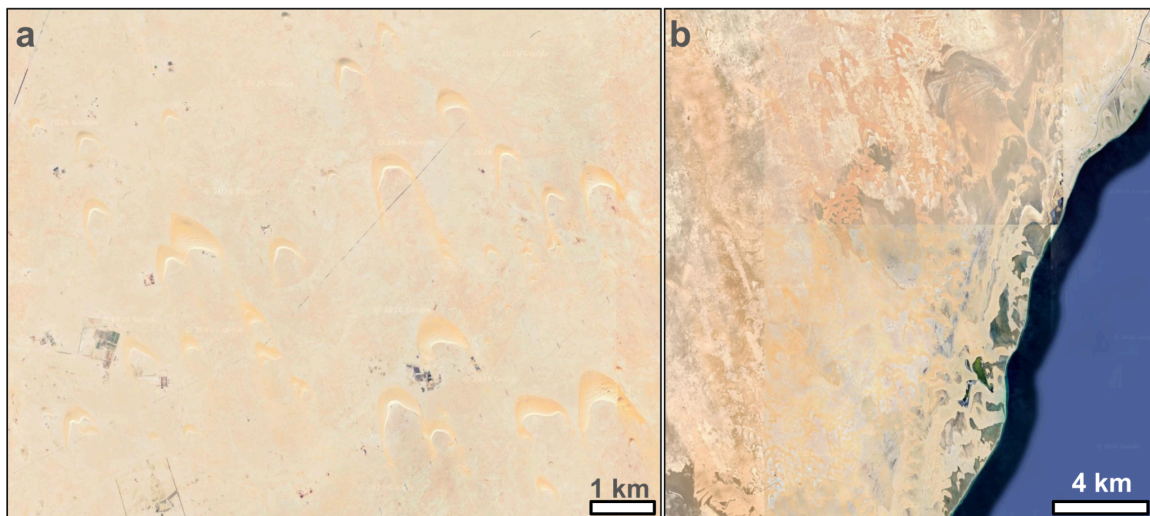
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### Supporting Information



**Figure S1.** (a) Inland barchan dunes, and (b) barchans at coastal sabkha.

### Text S1. Dune brink

To estimate the height of a dune, one could calculate it from the slipface length, between the dune brink and its toe, assuming an angle of repose of  $34^\circ$ . We found that the dune brink position is not necessarily associated with the highest gradient magnitude. Additionally, gradient-based edge detection is highly dependent on the window size, particularly since dunes vary in size. To that end, we created a workflow to extract the locations of dune brinks, along with more precise locations of the toe and head. For each dune, we extended several lines, “threads” from the toe arc of the dune contour to its head arc approximately at the middle (Figure S2A). Next, we extracted the

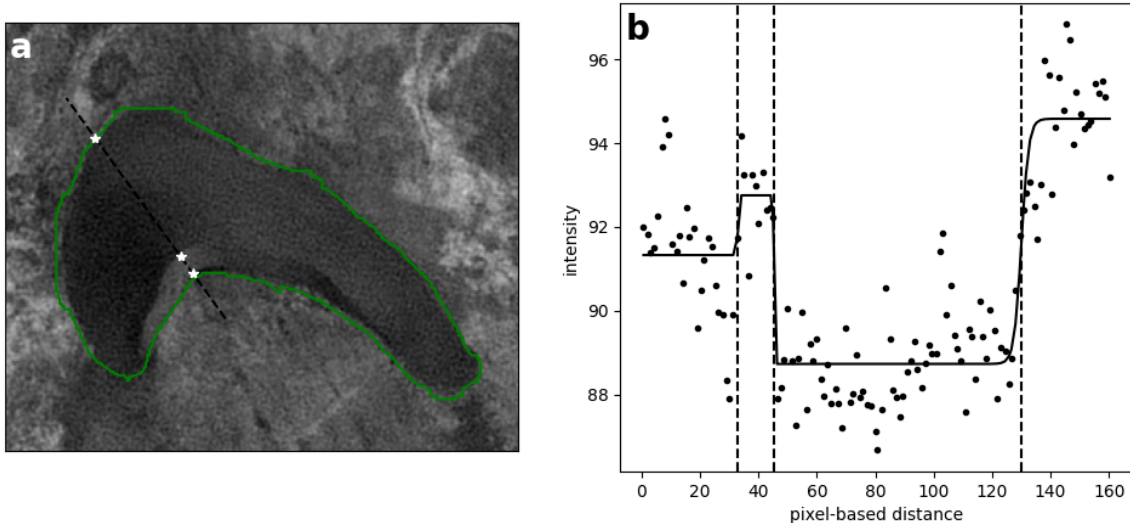


profile of image intensity values along each line and fitted the profiles with the hyperbolic tangent function (equation S1).

The hyperbolic tangent function has been found to effectively extract edge positions with subpixel precision (Nalwa & Binford, 1986; Cantatore et al., 2009). The extended threads provide a method for identifying where in the image to place the function. Assuming the presence of three edges, the amplitude terms ( $A$ ) in equation 1 describe the magnitude of the edge size, the slope terms ( $B$ ) describe the edge gradient, and the position terms ( $C$ ) locate the positions of the toe, brink, and head (Figure S2B). To solve the seven parameters in each profile, we used a constrained optimizer. To help the fitting converge, we used a piecewise linear regression to locate the sharp edges as initial values for the position terms. Also, we used bounds for both the position and slope terms, assuming, for instance, that the brink is located in the first half of the profile. To remove erroneously fitted parameters, we performed several checks. These included filtering outliers in the amplitude and position parameters locally and globally. We also kept only threads with brink and toe locations that matched the piece-wise linear regression within 2 pixels. Despite this check, we found that the hyperbolic tangent fit is better overall than the piecewise linear regression, particularly for estimating the head location. Also, we included only fitted parameters with amplitudes with consecutively opposite signs. Finally, for each dune, we used the fitted parameters with the smallest fitting residuals among the remaining threads.

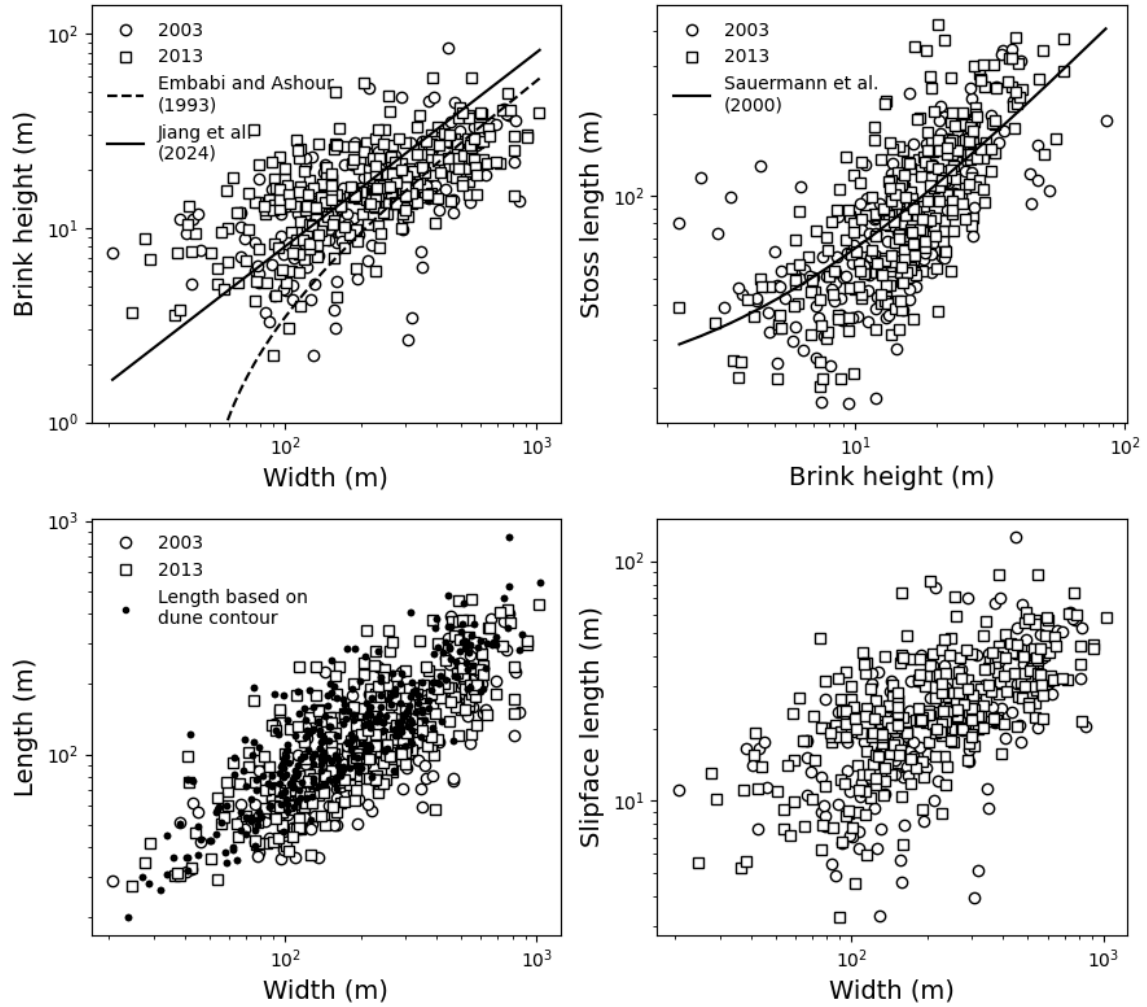
$$y(x) = A_{toe} \tanh(B_{toe}(x - C_{toe})) + A_{crest} \tanh(B_{crest}(x - C_{crest})) + A_{tail} \tanh(B_{tail}(x - C_{tail})) + D$$

(equation S1)

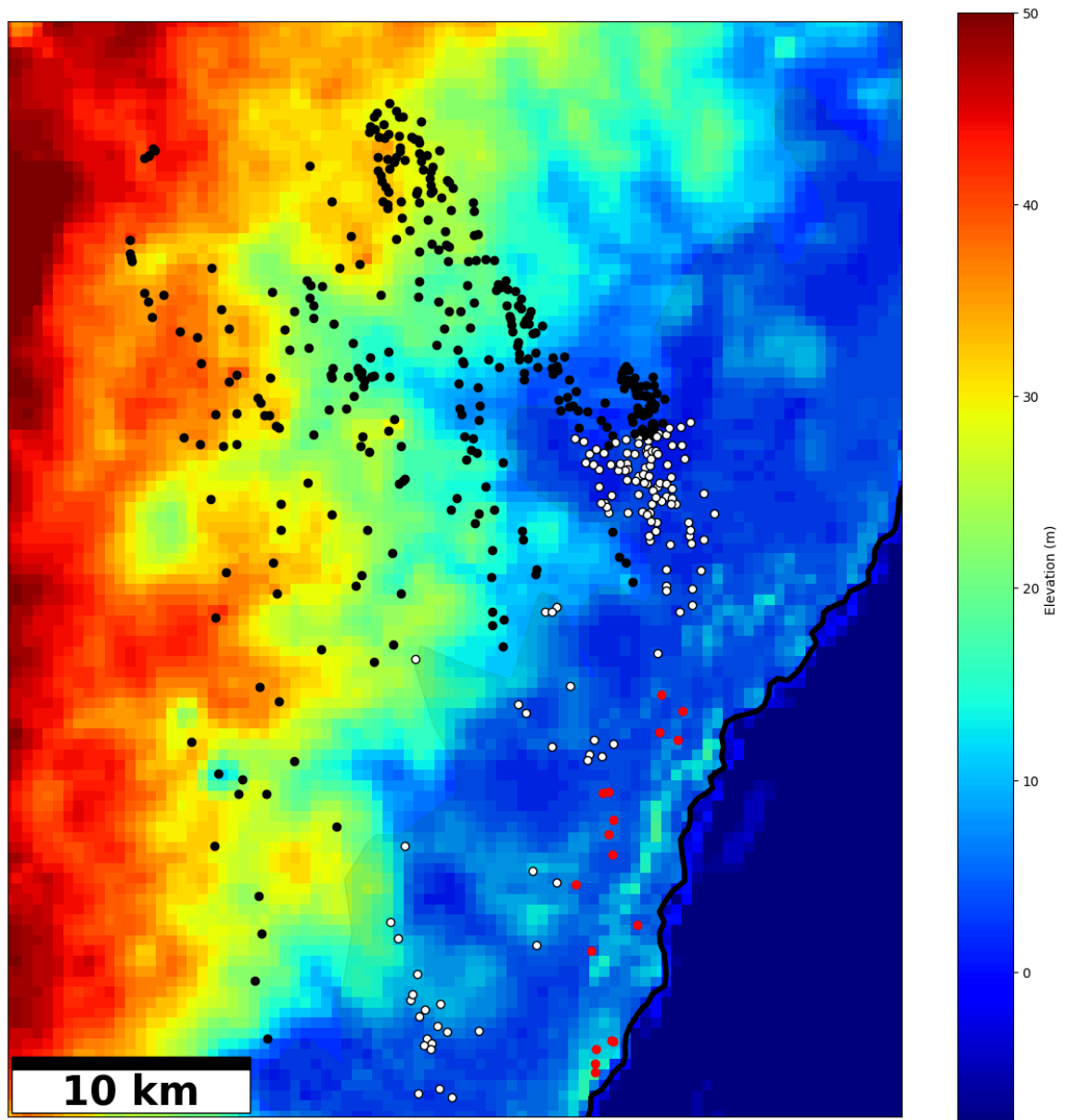


**Figure S2.** Example of locating toe, head, and brink positions based on tanh fitting. (a) An image crop of a barchan with the toe, brink, and head position (white stars), and a

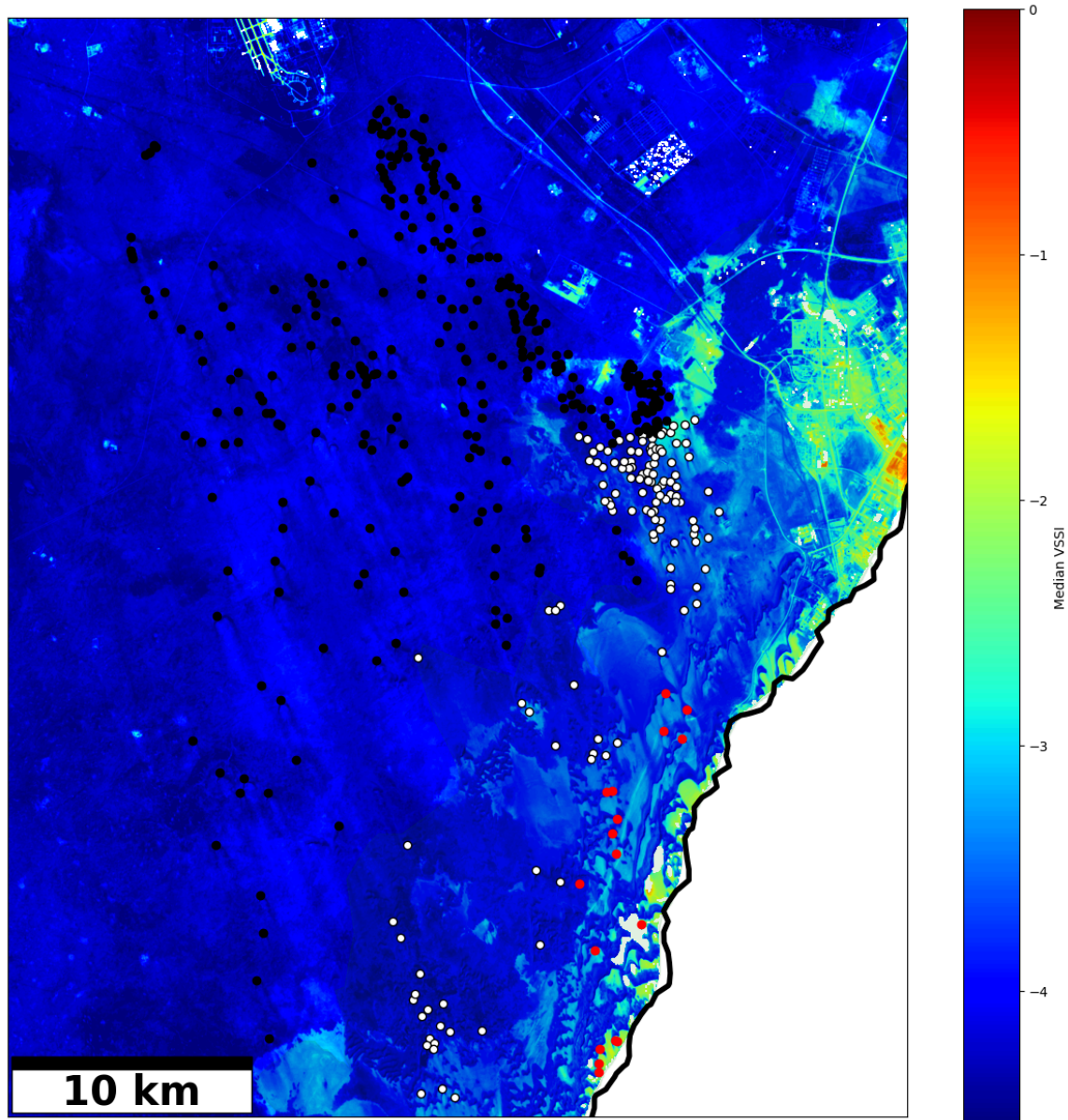
thread, extended by 30%, chosen after filtering noisy fittings. (b) The profile of image intensity versus the distance in image coordinates, with the feature positions (vertical dashed lines), arranged from left to right as toe, brink, and head.



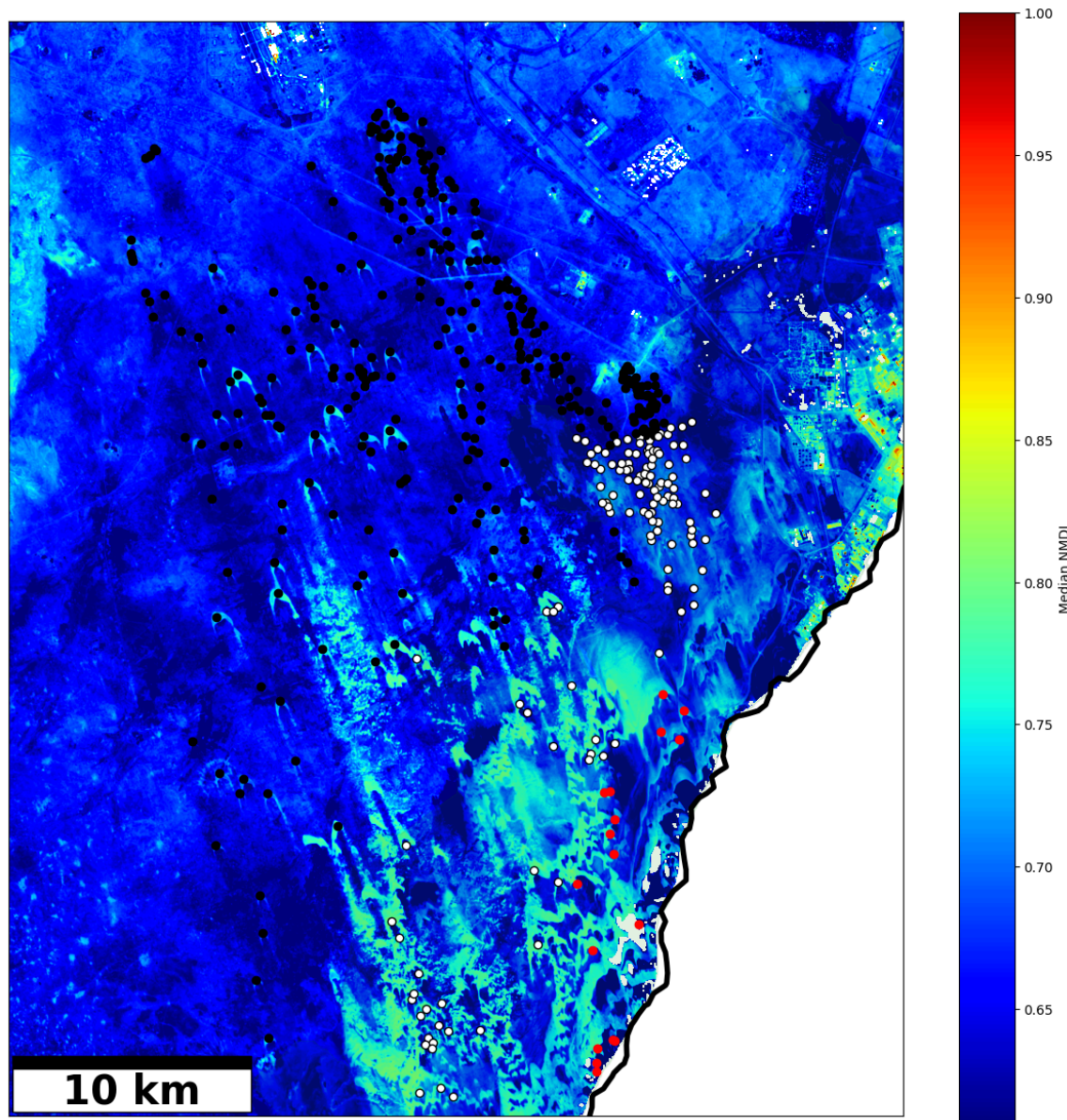
**Figure S3.** Calculated brink height, dune length, slipface length, and stoss length based on tanh fitting. Trends across the different parameters generally align with empirical fits reported in other studies in Qatar, China, and Morocco.



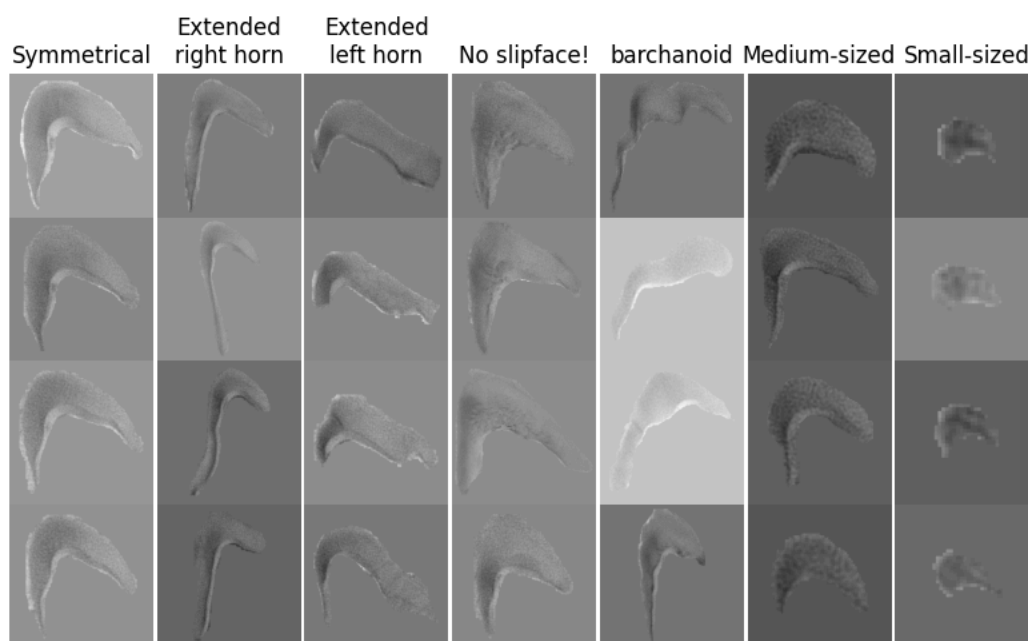
**Figure S4.** Classification of barchans as inland (black), sabkha (white and red), and within 4km from the coast (red). Sabkha extent is shaded in light green. The background is an elevation map (m) (GEBCO Compilation Group, 2023)



**Figure S5.** Classification of barchans as inland (black), sabkha (white and red), and within 4km from the coast (red). The background is Landsat median VSSI.



**Figure S6.** Classification of barchans as inland (black), sabkha (white and red), and within 4km from the coast (red). The background is Landsat median NMDI.



**Figure S7.** Barchan image crops (resized to a 448×448 shape while keeping the aspect ratios) that were first converted to embeddings with DINO encoders, and then grouped based on cosine similarity. Results show promise in grouping and pairing dunes with similar textures and features.

## CHAPTER 5: SHUTDOWN OF AEOLIAN SAND FLUX BY INFILL OF THE ARABO-PERSIAN GULF CONSTRAINED FROM BACK-MIGRATION OF BARCHANS IN QATAR

HUSSAIN ALQATTAN AND JEAN-PHILIPPE AVOUAC

### Abstract

Barchan dunes are ubiquitous on planetary surfaces and provide insight into the geological and environmental conditions under which they formed and evolved. Here, we showcase how remote sensing observations, which can be used to identify barchans and measure their migration rates, might be used to that effect. The study is focused on Qatar, where mineral assemblages show that the barchans have incorporated aeolian sand from the Zagros orogeny across the Arabo-Persian Gulf. The presence of wind-blown dunes exclusively in the south-east in Qatar, driven by the north-western Shamal winds, suggests that the filling of the Gulf due to post-glacial eustatic sea level rise has shut down their sand source. We use the migration velocities of 294 dunes to backpropagate their positions to examine whether their upwind positions back in time coincide with the time the sea level reached the present-day coastlines. We impose a rule whereby small dunes are merged if they intersect larger dunes as they are propagated back. Our analysis reveals that the first arrival of dunes is about 4.7ka BP. Further backpropagation confirms migration of the paleo-dune field across the upper section of the emerged floor of the Gulf and Zagros-derived sand sourcing. Accounting for changes in migration rates in space and time due to a possible increase in wind intensity, or reduction of dune mobility due to moisture or vegetation, we found that the shutdown of the sand flux could have occurred between 3.9 and 5.8ka. This confirms that the flooding of the Gulf estimated independently from geochronological data, 5-7ka BP, is probably the cause of sand flux shutoff.

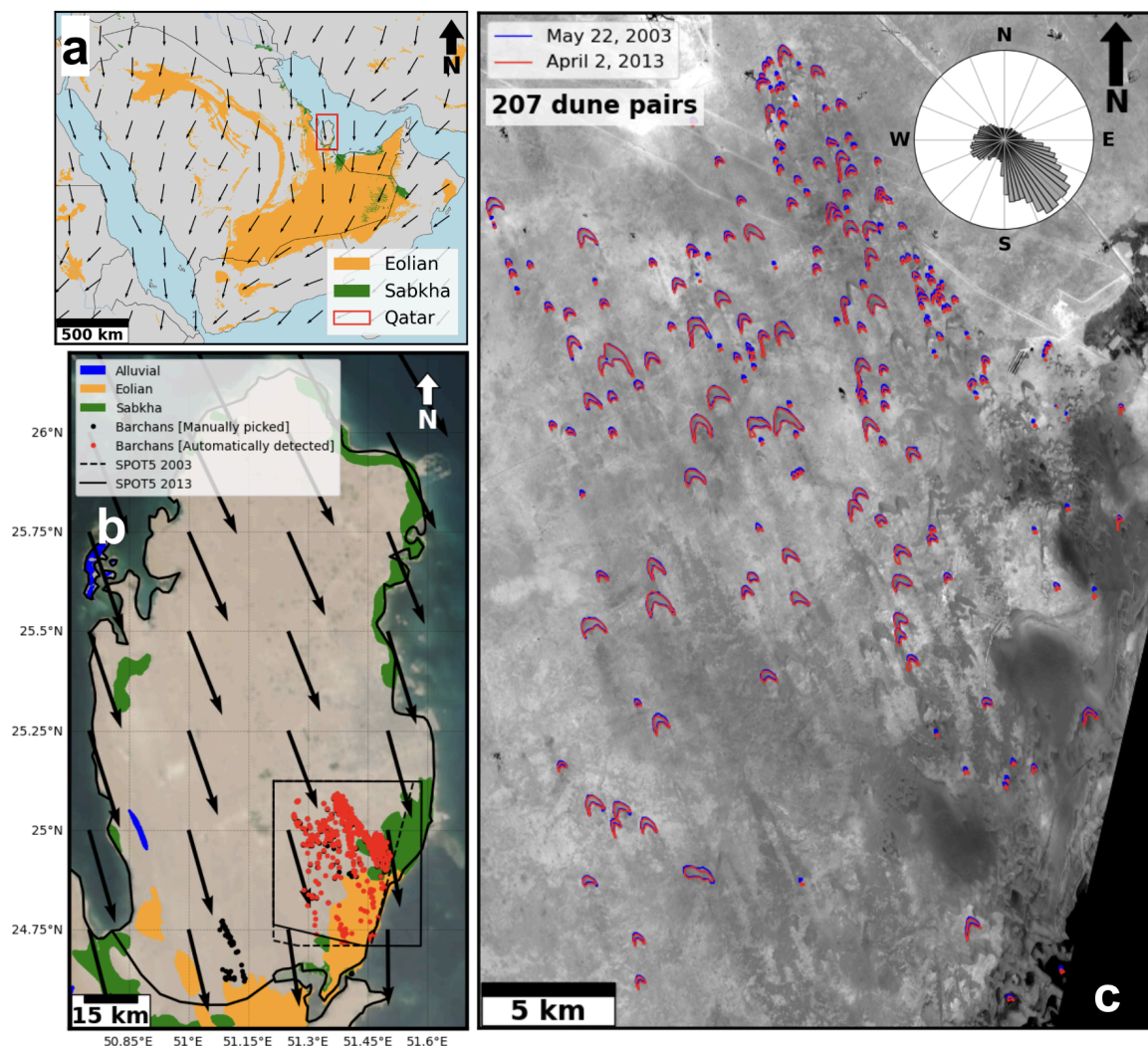
### 1 Introduction

Aeolian dunes are ubiquitous on planetary surfaces and can be used to infer the wind strength and direction that shape and move them, or the geological events that led to their formation and evolution (e.g., Hesse, 2009; Bourke et al., 2010). Barchan dunes, in particular, are ideal bedforms in that regard as they typify a simple unimodal wind regime, can respond relatively quickly to changes in boundary conditions, and can be identified and tracked relatively easily using satellite optical images (Vermeesch and Drake, 2008; Leprince et al., 2008; Vermeesch and Leprince, 2012; Ewing, 2015).

The arid surface of Arabia is covered by various types of dune morphologies that extend from the Arabian Shield front west of Saudi Arabia to Rub' AlKhali south to the



coasts of the Persian Gulf east (Figure 1A). The dunes of Qatar, located at the northern boundary of the dune fields of Arabia, are particularly interesting (Figure 1B). They are only present in the south of the peninsula (Figure 1B; Shinn, 1973; Embabi and Ashour, 1993; Al-Ansary et al., 2012; Al-Awah and Matter, 2023). They consist of carbonate-rich sands with epidote-amphibole-pyroxene heavy minerals, indicating sourcing from the Bitlis-Zagros orogeny (Garzanti et al., 2013). For comparison, sediments sourced from the Arabian shield are richer in quartz, with heavy mineral assemblages containing zircon, rutile, and tourmaline (Garzanti et al., 2013). The rest of Qatar is covered mostly with Eocene carbonate sediments, Pliocene coarse-grained fluvial sands, and sabkha deposits along the coasts (Figure 1B; Shinn, 1973; Al-Saad, 2005; Al-Ansary et al., 2012).



**Figure 1.** Sand Cover in Arabia and Qatar. (a) Border map of Arabia showing aeolian sands (isolated barchans not necessarily included) and Sabkha cover, regional wind directions, from ERA5-Reanalysis data (Hersbach et al., 2020), and Qatar location. (b)



Map of Qatar showing the southern dunes with aeolian and sabkha cover, barchans, and the areal coverage of satellite images used for barchan migration measurements. (c) SPOT5 satellite image, showing the automatically detected outlines of barchan dunes from the two images, from May 22, 2003, and April 2, 2013, and a rose diagram of in-situ wind measurements. The Barchan fields are restricted to a limited area of southeast Qatar and transition to a nearly continuous sand sheet toward the coast. In (b), there are barchans, black dots, manually picked in Google Earth images, but not included in the study because they fall outside the satellite images used for migration measurements. However, the upwind edge of these dunes is several kilometers downwind from the barchans in our study.

There is currently no coastal sand accretion from seacurrent along the northern coast, an observation consistent with the absence of a source of aeolian sand at present (Cavelier, 1970; Embabi and Ashour, 1992). It is thus likely that these aeolian sands were transported to the peninsula from the Zagros Mountains at a time when the floor of the gulf was emerged. The Gulf has experienced intermittent emergence during glacial times. The Gulf floor was exposed during the LGM (~20ka), when the sea level was below -120m, hosting the extension of the Tigris-Euphrates river system. Archaeological studies of the 'Ubaid pottery suggest a riverine network with marshes and freshwater lakes (Cuttler, 2013; Walkden and Williams, 1998). Following the LGM, sea level rose, filling the Gulf at a constant rate until the mid-Holocene (Lambeck, 1996), cutting off any aeolian sediment input from the Gulf landward, and rose to a highstand marked by beach deposits observed ~2m above present sea level (Shinn, 1973).

Because the surface of Qatar upwind of the barchan dunes is free of dunes for a distance of more than ~90 km until the northern coast, several studies hypothesized that the filling of the Gulf during the mid-Holocene caused the cutoff of the source supplying sand to the dunes (Shinn, 1973; Kassler, 1973; Doornkamp et al., 1980; Sources within Al-Hinai, 1987). The dunes kept migrating southeast, while submerged dunes never followed along, presumably stabilized and reworked by the rising sea level. This has been corroborated by recorded observations of relic dunes submerged along the coast of the Gulf of Salwa, west of Qatar (Kassler, 1973; Doornkamp et al., 1980; Al-Hinai, 1987). In this study, we test this scenario based on the current migration rate of the dunes, as measured from remote sensing observations (Michel et al., 2018). Hereafter, we first describe the methodology used to backpropagate the dunes, and next we discuss the results in view of the geophysical and geological information on the submergence of the Gulf.

## 2 Methods

To estimate the present-day migration rate of the barchans, we measured their displacements using the panchromatic bands of two SPOT5 satellite images (Figure 1C),

acquired on 22 May 2003 and 2 April 2013, with a resolution of 2.5m. The ~10-year time span should allow for representative average measurements of migration rates. These images were already orthorectified and co-registered with a subpixel accuracy (Michel et al., 2018).

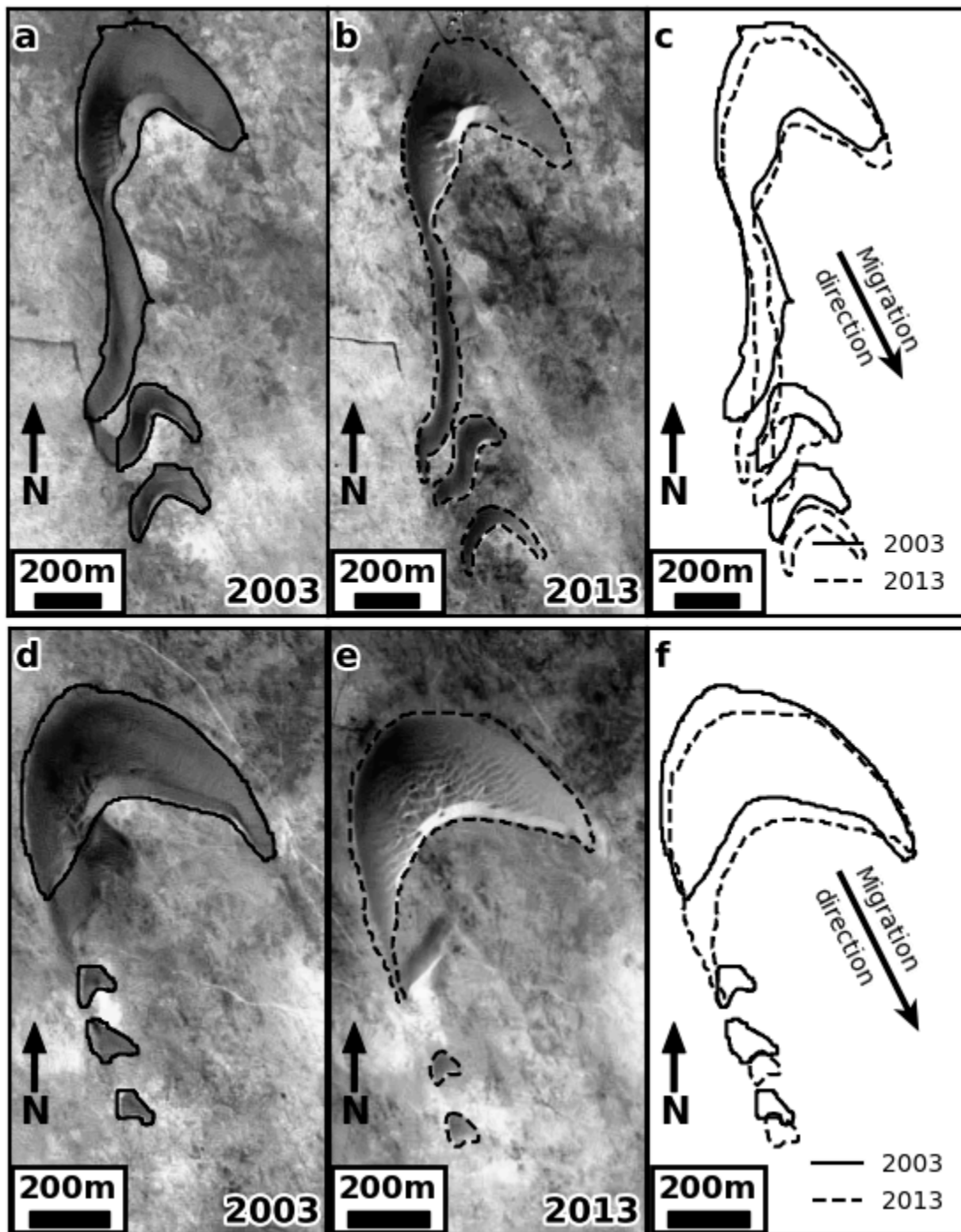
In each image, we extracted the boundaries of isolated barchan segmentation using an instance segmentation model, You Only Look Once (YOLOv11). The model was retrained from a smaller pre-trained version (Cunez et al., 2024). In addition to combining pre-labeled barchan image crops from both Mars (Rubanenko et al., 2021) and Earth (Cunez et al., 2024), a few image crops of the satellite images used in this study were included. After removing false positives, nearby dunes with ratios higher than 1:2 were paired. Using the difference between their centroid positions and the time span between the two image acquisitions, their migration rates were measured.

Because our method included projecting dune positions northwestward across the surface of dune-free Qatar, we investigated whether the wind regime or other local conditions varied considerably. Overall, the topography of Qatar has a low elevation and subtle roughness (Figure S1A). It has an arid climate with temperatures ranging from 20 to 36°C and a mean annual rainfall of between 13 and 62mm. Meteorological conditions along the trajectory of the dune field from the southern to the northern coasts are pretty uniform. Still, wind magnitude increases by ~0.5m/s, wind azimuth shifts 10 degrees to the east, total annual precipitation increases by 5mm, temperature decreases by 1 °C, and topography increases, then drops by about ~50 m (Figure S1B).

To constrain the sand cut-off by the Gulf filling, we translated the dunes back in time, with one-year time steps, and registered the first date any dune exited the northern Qatar coastlines. Due to the relative homogeneity of the topography and climate in Qatar, the projection of southern barchan dunes back in space and time with no substantial modifications in migration velocity is justifiable (Figure S1). However, for a robust analysis, we experimented with different scenarios and alterations that may have diverted the behavior of the dune field and its migration rates from modern times.

For the first scenario, the dunes were backpropagated with their present-day sizes with no modifications. We observed that several dunes collided as they were propagated in time, with a clear indication that some had actually emerged from a larger dune (Figure 2). We therefore imposed a rule in the second scenario whereby dunes that intersect are merged into larger dunes, and the resultant dune has a larger size and a slower migration rate. Although interactions other than merging were not applied explicitly, other types of interactions were present implicitly. The two scenarios represent different ends of a spectrum in terms of dune-dune interactions. The rule of merging upon intersection applied in the second scenario is meant to reverse dune fragmentation into smaller dunes observed in the present-day field (Figure 2; Genois et al., 2013; Assis and

Franklin, 2020; Wiggs, 2022). On the other hand, the first scenario, by merely allowing dunes to pass through upwind dunes, incorporates sideswiping and sediment exchange (Vermeesch, 2011; Elbelrhiti, 2012).



**Figure 2.** Examples of dune fragmentation in Qatar. The cropped images from SPOT5 satellite imagery acquired in 2003 (a & d) and 2013 (b & e) show larger barchans and several smaller dunes emanating from their right-side horn. c & f) The same dunes displayed as contours that were detected and segmented with the YOLOv11 model from the two image epochs (2003 and 2013); the arrows show the migration directions.

To merge any dune pair, we used a fitted model between dune width and volume in Qatar (Michel et al., 2018) to first convert dune widths into their respective volumes. Next, we added their volume and converted the new volume back into width. The new width was then used to calculate the migration rate of the new dune using another fitted model based on manual displacement and geometrical measurements of a segment of the dunes in Qatar, about 60 dunes (Michel et al., 2018). For the third scenario, instead of variable migration rates, we assumed the dune field moved as a whole with the same rate for all dunes, which we chose to be the 50th, 75th, and 95th percentile rates. Since all dunes moved at the same rate in the third scenario, they never intersected, maintaining the same spacing.

Furthermore, for each scenario, we modified the migration magnitude by 10% and 20% to account for the possibility of reduced or heightened sand mobility in the mid-Holocene. Conditions that may have lowered migration rates include reduced wind regimes or enhanced stabilization mechanisms and bed roughness (e.g., due to increased humidity and vegetation cover). In contrast, higher migration may reflect stronger winds during the earlier Holocene. We also assume that these speed modifications incorporate all possible sources of error, whether inherited from measurements (e.g., resolution of satellite imagery, imperfect dune boundary segmentation, inaccurate coastline positions), or local and temporal variability (e.g., interannual fluctuations, secondary wind effect). In all scenarios and modifications, we presumed dunes migrated in a steady state (i.e., no net volume change) unless a collision took place.

### 3 Results

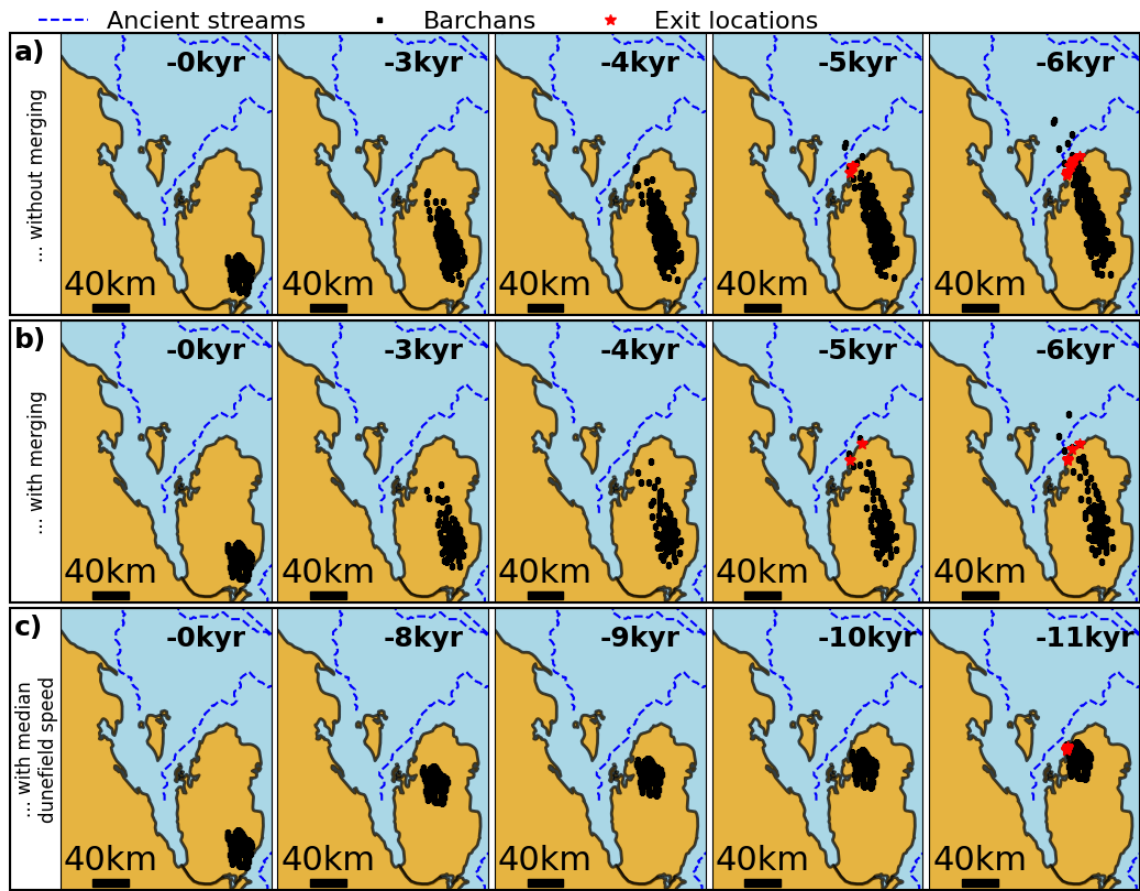
Out of a total of 482 isolated barchans, 294 dunes were paired and used in this study. They ranged in width between 31 and 990m, with a median width of 204m (Figure S2A). Their median speed was 9.3m/yr, ranging between 0.5m/yr and 27.6m/yr (Figure S2B). Although barchans encode their migration direction in the trajectory of their crest and horns, the local heterogeneity of the wind regime and the underlying surface can deviate the observed internal azimuth of the dune from the general migration direction. This heterogeneity could also affect the direction in which dunes migrate. The 2nd-98th percentiles of the internal and migration azimuths of dunes were 142°-169° and 130°-202° degrees, respectively. However, to avoid propagating errors and the effect of local variability in both the internal azimuths of dunes and their migration azimuths to

the backpropagation trajectories, we used the median field migration azimuth ( $162^\circ$ ) as the overall migration direction of all dunes.

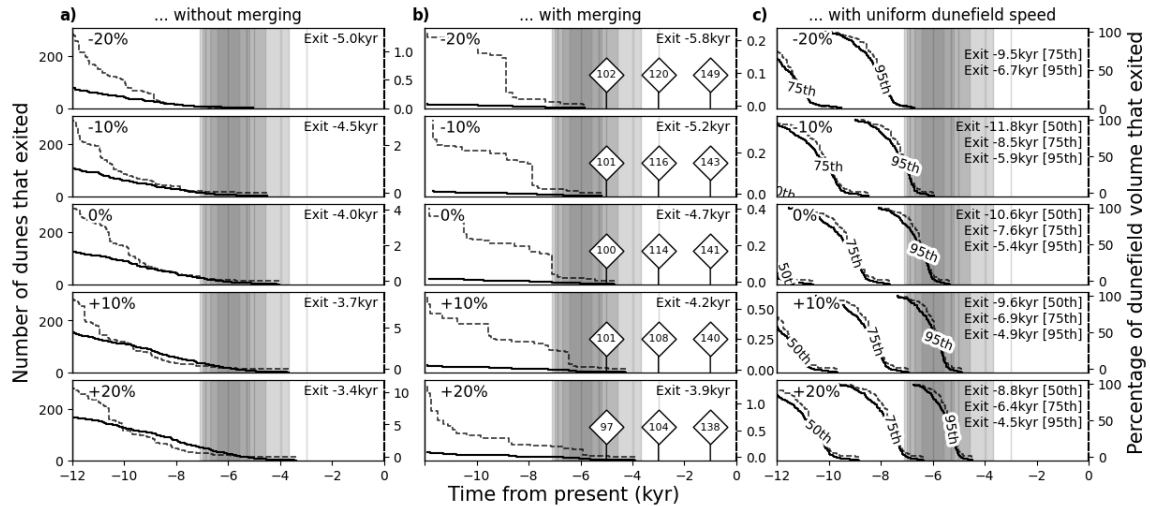
The total volume of paired dunes is about  $110.5 \times 10^6 \text{ m}^3$ . Their size and volume distribution in the field are not uniform (Figure S3). Most dune pairs are in the upwind and eastern segment of the field. Dunes are less clustered downwind, with greater interspacing, until they emerge at the coastal sabkhas, forming compound and transverse dunes (Figure 1C), which are not included in this study.

The measurements show that the migration velocity is inversely proportional to the dune size (Figure S2C). This scaling is expected if the dunes are assumed to migrate with a steady-state geometry and uniform saturated sand flux (Michel et al., 2018). A uniform saturated sand flux makes sense given that the dune field must experience a rather uniform wind regime (Figure S1A) and has uniform properties (e.g., grain size distribution) (Al-Awah and Matter, 2023). The southeastward migration direction is consistent with the morphology of the dunes and with the northwestern direction of Shamal winds that formed them, which blow at about 2 m/s (Figure S2A), mainly during Spring and Winter (Garzanti et al., 2013; Embabi & Ashour, 1993).

Our first back-propagation scenario indicates that the first dune would have reached the northern coast of modern Qatar about 4.0ka BP (Figure 3A). As expected, the interspacing between the dunes increased, with the smallest dunes crossing the coast first. By 7ka BP, about 24 dunes and a volume fraction of about 0.04% of the field volume had crossed (Figure 4A). Because dunes were allowed to cross other dunes without merging, the arrangement of exit time was dependent on the size distribution of the field (Figure S4A). As such, even dunes positioned on the southern coast reached earlier than upwind dunes.



**Figure 3.** Dunes distribution back in time after backpropagation based on modern migration rates, assuming (a) no dune merging, (b) with merging of dunes that cross paths, or (c) with the 50th percentile (median) speed used for all dunes. With this reconstruction, the dunes started crossing the northern coast around (a) 4,039 years ago, (b) 4,675 years ago, or (c) 10,614 years ago. This date would mark the time when sea-level rise in the Gulf shut down sand flux along the modern northern coastline.



**Figure 4.** The effect of varying the backward migration rates of the barchans (-20%, -10%, +0%, +10%, +20%) on the number of dunes (solid line; left axis), and percentage of dune field volume (dashed line; right axis) that cross the northern coasts, when using: (a) measured migration rates without merging, (b) after correcting for merging, or (c) uniform migration rate for all dunes. In panel b, because dunes merge, their total number changes over time, as shown by the diamond markers at selected times. In panel c, the uniform migration rate of all dunes is set as the 50th, 75th, and 95th percentiles. A factor, as indicated in the upper-left corner of each plot, is added to the migration rates, which increase from top to bottom. There is a linear trend between migration rate and the first arrival of dunes on the northern coast, as shown in the upper-right corner of each plot. In all plots, the gray-shaded regions indicate the range of geochronological dates that constrain the high stand of the Gulf, with darker shading for greater overlap.

In contrast, when intersecting dunes were merged in the second scenario, the first dune reached the coast at about 4.7ka BP (Figure 3B). By 7ka BP, about nine dunes have crossed the coast, and about 0.14% of the field volume, with larger interspacing than the first scenario. Moreover, the number of dunes shrank to half of its initial number within the first 1ka BP, with dunes from across the downfield stretch of the study area merging (Figure S5). Still, the faster upwind dunes were not the only ones that did not merge. When comparing the sizes of dunes that merged, most of them had a ratio lower than 0.5 to the larger dunes they merged into (Figure S6A). This observation aligns with findings suggesting that dunes with low size ratios (below 0.5) have a higher probability of merging (Genois et al., 2013; Assis and Franklin, 2020; Wiggs, 2022). For dunes that did not merge, their average width was 247m, while the average widths of parent and child dunes that merged were 453 m and 210 m, respectively (Figure S6B). Still, the position of interaction might lead to sideswiping rather than merging (Gay, 1999).

Also, as expected, mostly dunes in the upwind portions reached the northern coast first, followed by downwind and interior dunes (Figure S4B). For instance, dunes in the eastern portions of the dune field reached first since they do not have dunes upwind of them. Still, several dunes in the upwind front were superseded by faster downwind dunes, which indicates, based on this scenario, that dunes in the field are not necessarily arranged according to their age of formation.

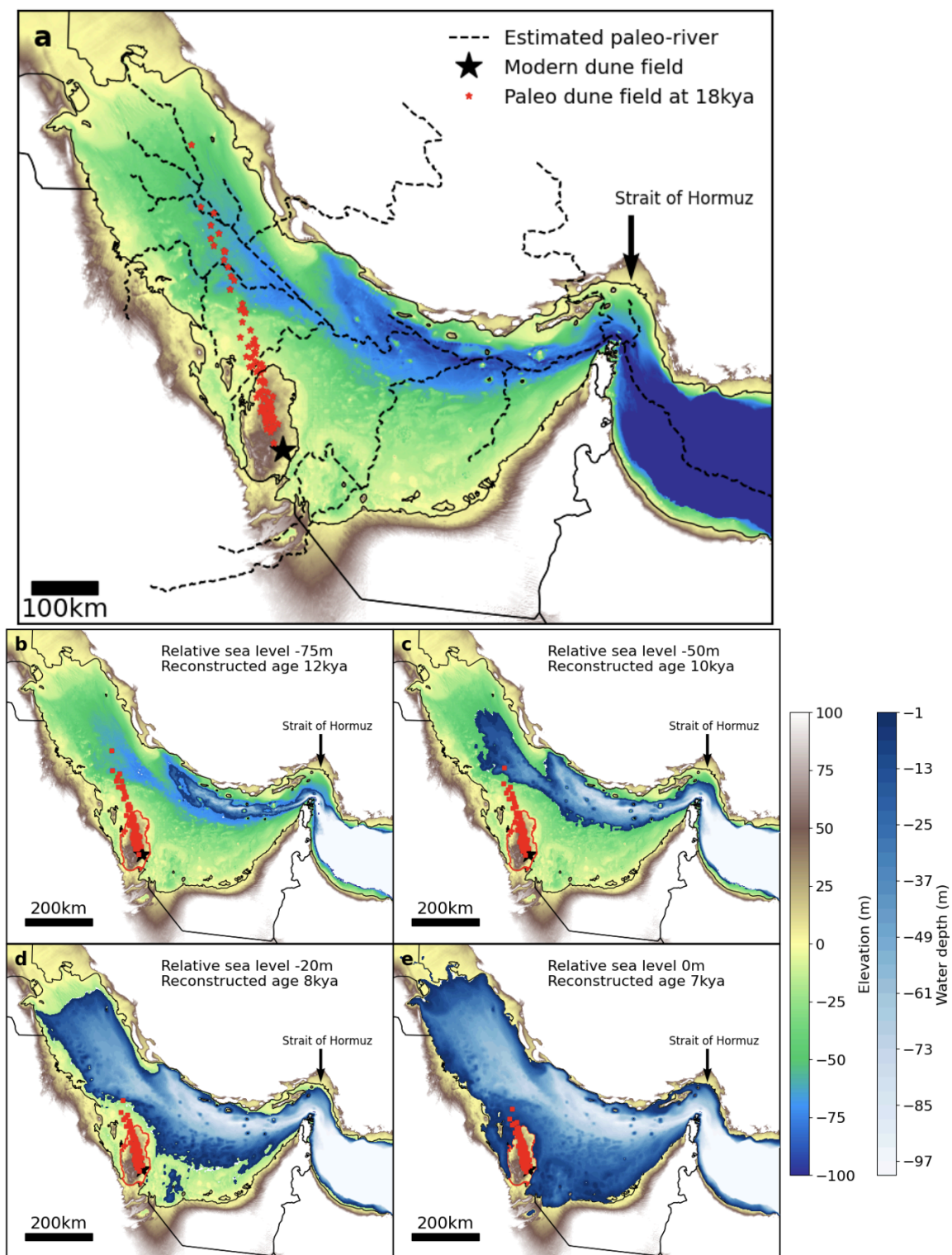
When the dune field moved uniformly with the median speed, the first dune did not reach the northern coast until more than 10.6ka BP (Figure 3C). When the speed was set as the 75th percentile, the first dune reached at 7.6ka BP, while with the 95th percentile as the uniform speed, the dunes reached the coast at 5.4ka BP (Figure 4C). The dune exit times were set by their modern positions (Figure S4C). With the same interspacing maintained, the entire dune field was at the coast at the time of first exit rather than spread across Qatar as in the other two scenarios (Figure 3). As such, the interspacing between the dunes was the lowest in the third scenario, with dunes crossing the coast at a median time spacing of 8 years, compared to 60 years in the first scenario, and 346 years in the second scenario when dunes were allowed to merge (Figure S7).

The effects of variable modifications to dune migration rates of 10% and 20% were non-linear and asymmetric across the different scenarios. The first dune exit was between 5.0 and 3.4ka BP for the first scenario, and between 5.8 and 3.9 ka BP when merging was allowed (Figure 4A; Figure 4B). This shows that a potential 10% slowdown or speedup in migration rates would have delayed or accelerated the first dune by about 500 or 300 years, respectively, in the first scenario. When dunes merge, the spacing between the dunes increases, resulting in 500-600yrs delay for each 10% slowdown, and a 300- 500 yr advance in exit time for each 10% increase in migration rates. Also, rather than a gradual exit, pulses of cumulative volume from merged dunes are observed to cross the coast simultaneously in the second scenario (Figure 4B). With uniform migration rates, the delay or speed-up in exit time was smaller with faster migration (Figure 4C). The dune field reached the coast between more than 12 and 8.8ka BP when it migrated at median rates, while it reached it between 9.5 and 6.4 ka BP at the 75th percentile rate, and between 6.7 and 4.5 ka BP at the 95th percentile rate. The entire dune field crossed the coast within about 2 kyr from the exit of the first dune at the 95th percentile, extending to more than 4 kyr at median migration rates.

It was hypothesized that, rather than being sourced from paleo-rivers along the Gulf valley, the quartz-rich aeolian sands had been transported from Arabia across the Gulf of Salwa and Bahrain before the submersion of the Gulf (Kassler, 1973; Shinn, 1973; Seltrust Engineering, 1980; Doornkamp et al., 1980). To that end, we investigated whether the dunes were generated by the river network running along the Gulf axis or transported from Arabia west of the Gulf of Salwa (Figure 1A). Using a Python-based



library (pysheds), we generated the steepest-descent stream network draining modern bathymetry (Figure 5A).



**Figure 5.** Comparison of the location of the paleo coastline (Lambeck, 1996) and the location of the backpropagated barchans prior to 7 ka BP. (a) Reconstruction at 18 ka BP when the global sea level was lower than the elevation of the seafloor at the Strait of Hormuz. The stream network was estimated using the steepest descent algorithm on the modern bathymetry of the Gulf. (b) Sea-level boundaries at different times since the last glacial maximum (Lambeck, 1996), overlaid on present-day bathymetry. Notes: Barchans propagated back in time suggest they originated from the Gulf axis. This pathway supports sourcing of sediments eroded in the Zagros and transported to the floodplains of the then-emerging floor of the Arabo-Persian Gulf. The upwind extent of the dune field generally aligns well with the reconstructed sea levels.

#### 4 Discussion

The geochronological data agree with a precision between 0.5-2k on the time when the Gulf reached its present-day and high-stand sea levels (Table S1). Even though the mechanism behind the sea level rise is understood, disagreement is largely influenced by the variability of used methods, and their differing levels of uncertainty and assumptions, in addition to the variability of shoreline position both in time and space due to local variability in active sedimentary processes, and both sea levels and topography (Woodroffe and Horton, 2005; Parker et al., 2020; Mauz et al., 2022). However, it seems that present-day sea levels were reached following a high-stand transgression sometime between 5 and 7 ka BP (Table S1; Figure 4; Bibby, 1973; Ridley & Seeley, 1978; Lambeck, 1996; Strohmenger et al., 2010; Lokier et al., 2015; Rivers et al., 2020; Parker et al., 2020; Rivers et al., 2020; Mauz et al., 2022).

The different scenarios with their modifications overlap in three time ranges: 4.5-5.0, 6.4-6.7, and 8.8-9.5 ka BP, in partial agreement with the geochronological age of 5-7ka BP. The agreement is better if dunes are merged and the cutoff timescale is not determined by the fastest dunes, especially if migration rates are enhanced. If the rates were larger, there would also be agreement if the timescale was determined by the 75% and 95% speeds. Though there was evidence in South Arabia, e.g., lake deposits in Rub' AlKhali, that the early Holocene was marked by wet periods (Bray & Stokes, 2003) most likely inducing vegetation growth and aeolian sand stabilization, it is not clear if the conditions associated with the increased monsoon and advancement of the ITCZ extended north to Qatar (Cuttler, 2013). Several periods of hyper-dry conditions were also recorded during glacier melt, which might have intensified dune mobility (Cuttler, 2013).

Moreover, since there was a highstand, 1- 3 m higher than present-day (Kassler, 1973; Lambeck, 1996; Strohmenger et al., 2010; Lokier et al., 2015; Rivers et al., 2020; Mauz et al., 2022), several dunes might have been trapped on the northern coast and got released upon regression, or remained as beach deposits before migrating and before

the establishment of Sabkhas, suggesting that the exit dates we found indicate delayed dune release. In Qatar and UAE, it was estimated that shoreline retreat exposed 3- 4.5 km of subaerial sandy beach and carbonate lands between 6.7 ka and 3 ka before reaching present-day levels (Rivers et al., 2020; Mauz et al., 2022). We also estimated similar landward lengths based on land areas of Sabkha (Figure S8). Dunes might have been trapped before 5ka BP; then, when sea levels lowered and sandy beach deposits were released, they migrated and joined the remaining dune field, delaying the apparent time when the sand source was cut off. Today, no sand accumulations are present on the northern beaches; instead, the coasts are covered with carbonate and sabkha deposits.

At the same time, the present-day status of aeolian dunes in the southern coasts could be the key to the past conditions in the northern coasts during high stand. There is no significant drop in wind strength near the southern coast to justify the stabilization and lower interspacing between the coastal dunes. Instead, a high stand, about 1ka BP at the latest, probably stabilized these dunes. Since the high-stand regression, the coastal dunes did not transform completely into barchans with the exception of few. The estimated time at which the dunes cross the current coastline thus provides, in principle, a lower bound on the time elapsed since the flux of sand was shut down by the immersion of the Gulf.

A few attempts were made using much smaller sample sizes to quantify the time of sand shutdown in Qatar (Embabi & Ashour, 1992; Engel et al., 2018). Previous reconstruction attempts using barchans either assumed that the cutoff time was determined by all the upwind dunes reaching the coast, with broad timescales between 3.3 and 17 ka BP (Engel et al., 2018), or just the smaller upwind dunes, resulting in an estimated timescale of 4.2ka BP (Embabi & Ashour, 1992). Although we constrain the sand cutoff to one dune, our reconstruction considers the entire dune field, using a more representative population sample extending to the southern coast, rather than only the upwind dunes. Also, as we observed when merging backpropagated dunes, the upwind edge of the dune field was not at the same distance from the coast, with some upwind dunes 5-10 km downwind of the others (Figure S4). Moreover, in our reconstruction, we examined the role of dune-dune interactions in altering the migration of the dune field and found that this accounted for about 500-800 years in the cutoff timescale estimate, improving agreement with the geochronological dates (Figure 3; Figure 4). Furthermore, the shutdown of the sand source might have led to a reduction in dune size, thereby overestimating their past migration rates and underestimating how long ago they crossed the coast.

The area ratios we calculated between merged dunes support the dominance of fragmentation in the dune field and the validity of the second scenario (Figure S6). While only the second scenario prevents dunes with upwind dunes from traveling back in time with their modern sizes, both scenarios lead to an arrangement of dune sizes that

decreases upwind, as often simulated in numerical models (Durán et al., 2011; Worman et al., 2013), and found in nature (Elbelrhiti et al., 2008; Day & Kocurek, 2018). It is possible that the dunes were smaller as they were released from fluvial floodplain deposits. This size distribution, in space and/or time, could indicate that they were faster near the northern shores or during the earlier Holocene, before merging and slowing as they migrated south.

Another possibility is that the dune field went through cycles of merging and fragmentation. The rates of merging and fragmentation would, respectively, increase or decrease the arrival timescale to the northern coast. In this case, the reconstruction timescale could be set by a balance between the smaller, faster dunes and the larger, slower dunes. In this case, similar to the third scenario, we assume that the reconstruction timescale is set by the velocity distribution of the entire field maintaining similar size distribution throughout their journey from the coast, starting with the median rate, where the larger dunes have higher control over the migration rate of the dune field, and the 75th and 95th percentile rates, where smaller dunes set the overall rate. Based on the dominance of fragmentation in the field (Figure S6) and the probable increase in wind strength as dunes back-propagated, higher percentile rates with modified migration magnitudes are more likely and are also in better agreement with the geochronological dates (Figure 4C).

The reconstructed river network in the Gulf valley shows a main trunk running along the axis of the gulf and could represent the location of the ancient extension of the Tigris-Euphrates river. The river network must have served as a conduit for transporting sediments from the Zagros Mountains through streams, incising the eastern side while spreading floodplain deposits across the Gulf valley (Walkden and Williams, 1998). Other major streams extend from the estuaries north of the Gulf and the ancient deltaic deposits south and north of Qatar. We used the relative sea level reconstructions from Lambeck (1996), superimposed on modern bathymetry (Figure 5B-E), to gauge the extent of gulf filling since the LGM. By 10ka BP, the central valley of the Gulf was overwhelmed, reaching present-day coastline levels between 6-7ka BP. The reconstructed coastlines suggest that the paleo-river floodplain still had an opportunity to generate sediments between 10ka BP and 8ka BP, before being cut off by 6-7ka BP (Figure 5). Overall, backpropagation results over the last 18k confirm that the sediment source for the dunes is most likely from the upper section of paleo-river floodplains in the Gulf, while dunes in eastern Arabia and the UAE might have been fed by the downstream sections of the paleo-river (Figure 5A). Still, dunes extending to the Gulf waters by 7ka BP support our hypothesis that, as dunes approached the northern coast, they were stabilized by a high stand or reduced mobility, delaying their migration.

In all scenarios, the propagated dunes would have crossed east of Bahrain to the axis of the Gulf, rather than initiating from Arabia (Figure 3). This suggests that the dunes most

likely originated from the paleo-river in the Gulf, extending north to the Zagros Mountains. However, our reconstruction of paleo-drainage networks shows drainage from Arabia to the Gulf of Salwa, connecting the sediment source from the Arabian Shield to the east (Figure 3; Figure 5). This connection, if fluvial flow was a reality at the time, suggests that any sourcing from Arabia cannot be ruled out, though it might have been transported by water rather than by wind. On the other hand, the bathymetry of the gulf (Figure 5) shows an overall steeper topography in the eastern half and a more gently sloping one in the western half, supporting greater transport potential from the Zagros in the east (Kassler, 1973).

By about 60ka BP, all of the dunes would have crossed the present-day northern coastline of Qatar (Figure S4; Figure S9). While these dunes are not the total volume of aeolian sand in southern Qatar, whether as subaerial dunes or as aeolian deposits (Shinn, 1973), the timeframe coincides with the time when the gulf valley was empty of water, going as far as 70ka BP, or even 100ka BP (Kassler, 1973; Cuttler, 2013). There seems to have been an inflection point at ~20ka BP (Figure S9), after which sand was transported at a faster rate than afterward. The sizes of the dunes were probably smaller closer to their source; hence, they traveled faster closer to the river floodplains. Coincidentally, the onset of sea-level rise has been estimated at about 20ka BP (Kassler, 1973). This could indicate either reduced sediment flux or higher efficiency in stabilizing the moving sand. On the other hand, in earlier times, between 40 and 25ka BP, sediment flux seems to have been accelerated. Since the Gulf only began filling at 18ka BP, other regional forces might have contributed to changes in the trend.

Although our study used the largest dataset on barchan migration in Qatar, providing insights into the use of barchan dunes to constrain geological events, some limitations remain. First, azimuth variations were excluded to avoid the effects of local variability on the backpropagation trajectory. The dunes that did not merge in the second scenario, but were not at the upwind edge of the field, could have been generated or fed laterally by nearby dunes (Figure S5), induced by secondary winds (Figure 1C). This could also explain why not all of southern Qatar is covered with dunes, as dunes can move laterally, at a lower rate, forming corridors. This also aligns perfectly with observations in other fields and with simulations in numerical models (Genois et al., 2013). While a good portion of the delta likely crossed to the other side of the lagoon, some probably migrated south to Saudi Arabia (Figure S8). Third, while interannual variations in migration rates have been observed before (Engel et al., 2018), the decadal time span (2003-2013) should average out these variations.

The dune pairs we used by no means include all the wind-blown sand in southern Qatar. In addition to unpaired barchans, there are sand sheets and barchanoids close to the coasts (Figure 1C). However, because these sand accumulations are at the downwind front of the field, they are less likely to have been the first to migrate from the northern

coast. Furthermore, while the satellite images we have cover most of the barchan dunes in Qatar, we have detected a swarm corridor south-west of Qatar that was not included in the study area (Figure 1B). The upwind edge of this swarm is further south than the barchan dunes in our study. This additional distance would further confirm our findings (Figure S8), since this corridor of barchan swarm is closer to the northern coast than the eastern dunes in the study area, and most likely was cut off at the same time.

There have been several studies that contemplated the behavior of dunes as a population, mainly using numerical models (Anderson, 1996; Hersen & Douady, 2005; Durán et al., 2008, 2011; Worman et al., 2013; Genois et al., 2013; Day and Kocurek, 2018; Robson et al., 2022; Day, 2022). The presence of variable dune sizes in all barchan fields is a testament that the various types of dune interactions maintain a self-organizing size distribution rather than merge into one cumulative dune or fragment into equally sized and spaced dunes traveling at the same speed (Worman et al., 2013; Wiggs, 2022). How the size distribution affects the migration rate of the field as a whole remains unknown. In the first scenario, as many would assume, small dunes determine the migration rate of a dune field. But this means that at some time in the past, small dunes were completely isolated from the field (Figure 3A). This does not seem likely unless different portions of the field had different sediment fluxes, fragmenting the field into subfields that follow one another.

It is also not known the effect of changes in boundary conditions on the migration rate of the field, as it was shown that the distribution and spacing of dunes seem to be influenced by changes in the boundary conditions (Elbelrhiti et al., 2008; Łopuch et al., 2022; Marvin et al., 2023). Since dune migration rates are proportional to their sizes, and the dune field maintains a specific size distribution, is the migration rate of dunes as a field random, or does it scale with changes in the size distribution? If yes, does it scale with the 50th, 75th, or 95th percentile?

Our analysis shows how the geological events that have shaped the formation and evolution of dunes can be inferred from dune migration rates. A similar approach could be applied to other planetary surfaces where geochronological dating is unattainable and without reliance on terrestrial empirical models (e.g., Ewing, 2006; Daudon et al., 2024). Furthermore, more extensive studies of large barchan fields, in addition to numerical modeling, could address questions about the roles of roughness elements, dune-dune interactions, and morphological changes in affecting the overall migration rate of a barchan dune field and could reduce the uncertainty of our approach.

## 5 Conclusions

Heavy-mineral assemblages from barchan dunes in southern Qatar indicate a quartz-rich sand source from the Zagros orogeny and transported via paleo-rivers through the Arabo-Persian Gulf valley. As such, the presence of aeolian sand cover exclusively in

southern Qatar implies their supply was cut off when the Gulf floor was submerged. Barchan migration offers an independent geomorphic record of this source shutdown. Previous studies using barchan migration were limited and inconclusive. Here, we compile the largest dataset of barchan migration rates from Qatar and back-migrate dunes to reconstruct when the upwind edge of the dune field first crossed northern Qatar, marking the cessation of sand supply. Across most scenarios and modifications, supply was terminated within 0.5- 1 ka of independent geochronological estimates.

We tested three scenarios to account for dune-dune interactions and variable mobility. First, if dunes migrated as solitary barchans, the upwind edge reached the coast ~4.0 ka BP. Second, allowing dune merging, consistent with field evidence for fragmentation, delayed this exit time to ~4.7ka BP. Third, if migration rates scaled with the overall dune-size distribution rather than with the smallest dunes, percentile-based rates (50th, 75th, 95th) yielded later timing (5.4-10.6ka BP). For each scenario, 10-20% changes in migration rates were applied to account for reduced/enhanced dune mobility in northern Qatar and back in time. When the smallest dunes determined the exit time, agreement with the 5-7ka BP geochronological window is achieved when dune merging is included and if dune stabilization is activated. When dune mobility is scaled by size distribution, higher percentile rates and stronger winds provide the best match. These results indicate that barchan migration can constrain the timing of the shutdown of sediment supply. This approach can be applied to estimate absolute timescales of environmental changes on planetary surfaces where geochronological data are not attainable.

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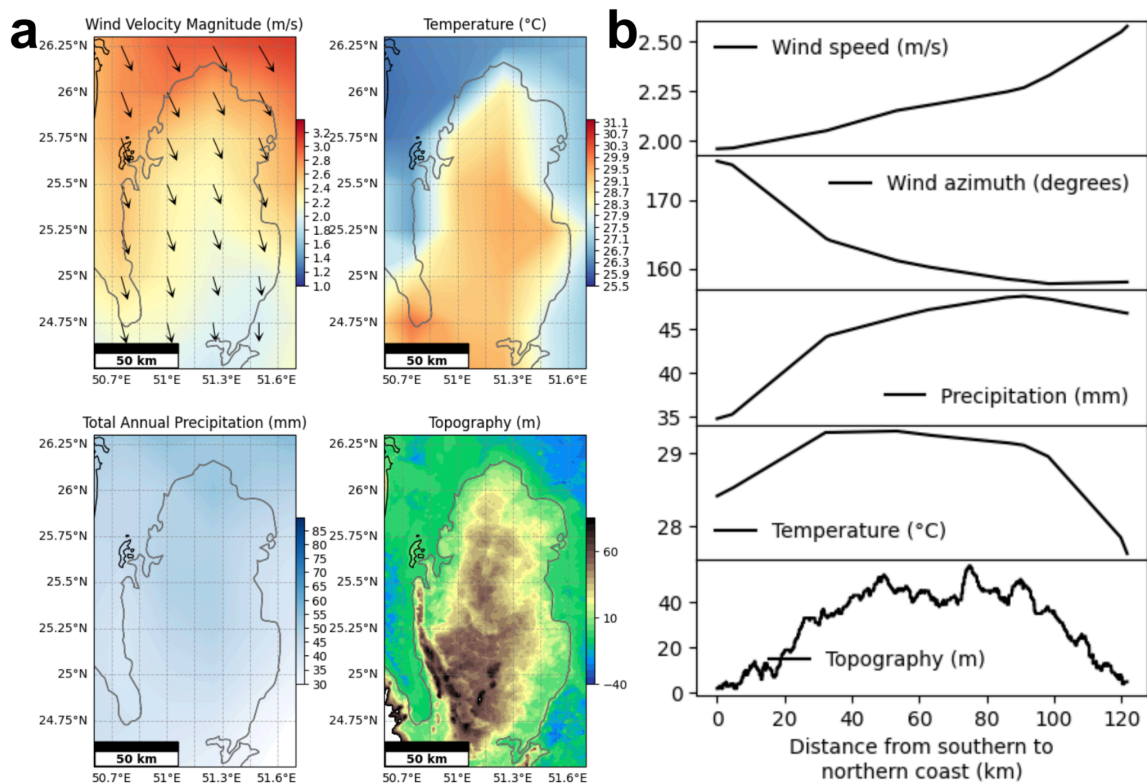
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## Supporting Information

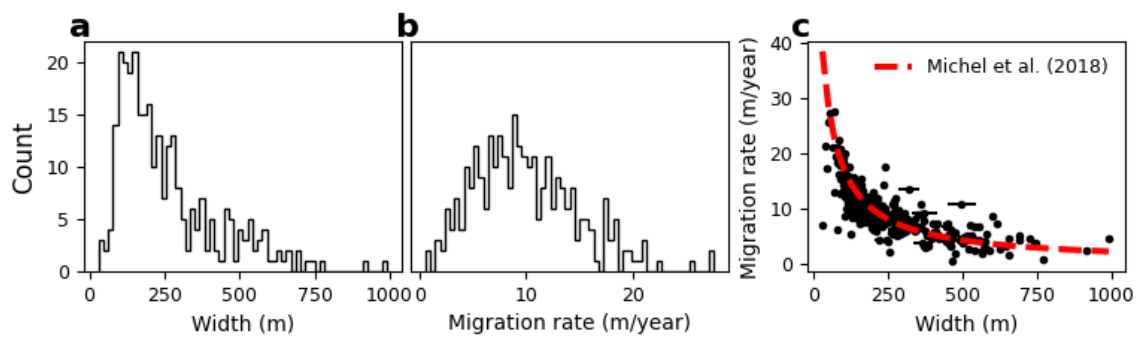
**Table S1.** List of geochronological and other methods used previously to constrain the filling of the Gulf.

| Date Start | Date End | Dating Method | Dated Event | Sample Location | Reference |
|------------|----------|---------------|-------------|-----------------|-----------|
|------------|----------|---------------|-------------|-----------------|-----------|

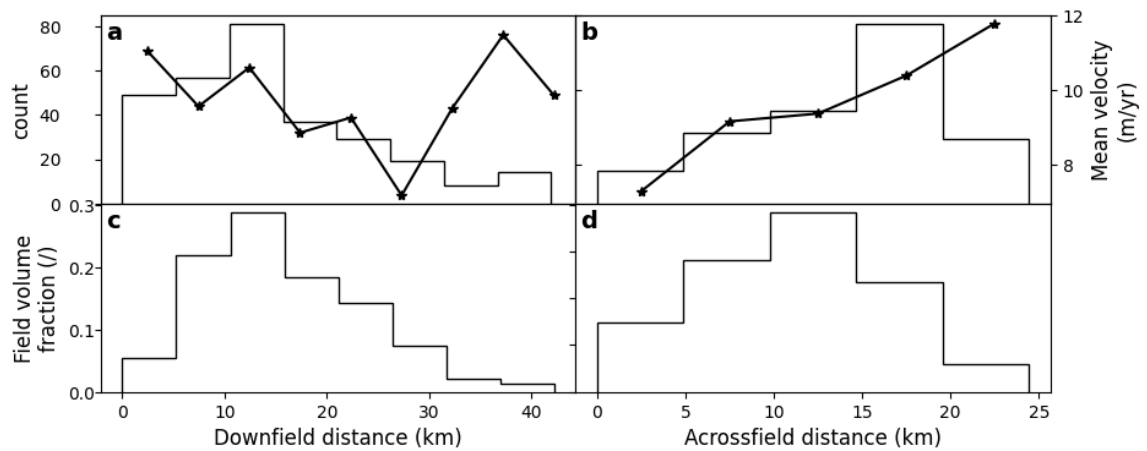
|      |      |                                                                                         |                          |              |                          |
|------|------|-----------------------------------------------------------------------------------------|--------------------------|--------------|--------------------------|
| 6890 | 7100 | C14 from Whale bones                                                                    | High-stand transgression | UAE          | Lokier et al., 2015      |
| 4570 | 5290 | C14 from Whale bones?                                                                   | Modern-day sea level?    | UAE          | Lokier et al., 2015      |
| 6000 | 6700 | Glacio-isostatic adjustment modeling, C14 dating of proxy carbonate facies distribution | High-stand transgression | Qatar, UAE   | Mauz et al., 2022        |
| 3000 | 3000 | Glacio-isostatic adjustment modeling                                                    | Present-day level        | Qatar, UAE   | Mauz et al., 2022        |
| 3667 | 3957 | C14 from beach shells                                                                   | High-stand transgression | Saudi Arabia | Ridley & Seeley, 1978    |
| 5000 | 6000 | Ubaid archeological sites                                                               | High-stand transgression | Saudi Arabia | Bibby, 1973              |
| 4000 | 5000 | Beaches                                                                                 | High-stand transgression | Qatar        | Taylor & IlUng, 1969     |
| 6000 | 6000 | Glacio-isostatic adjustment modeling                                                    | High-stand transgression | Oman         | Lambeck, 1996            |
| 5600 | 7000 | C14 of carbonate sands and corals                                                       | High-stand transgression | Qatar        | Rivers et al., 2020      |
| 5200 | 6400 | C14 dating of proxy carbonate facies distribution                                       | High-stand transgression | UAE          | Strohmenger et al., 2010 |
| 5310 | 6880 | C14 dating of proxy sabkha deposits and beach shells                                    | High-stand transgression | Saudi Arabia | Parker et al., 2020      |



**Figure S1.** Climatic setting and Topography of Qatar. (a) Wind velocity magnitude and direction, temperature, total annual precipitation, all calculated from ERA5-Reanalysis data and averaged in time between 2003 and 2013. (b) transects of the climate indicators and topography from the southern to the northern coast with a similar azimuth to the azimuth of the dune field.

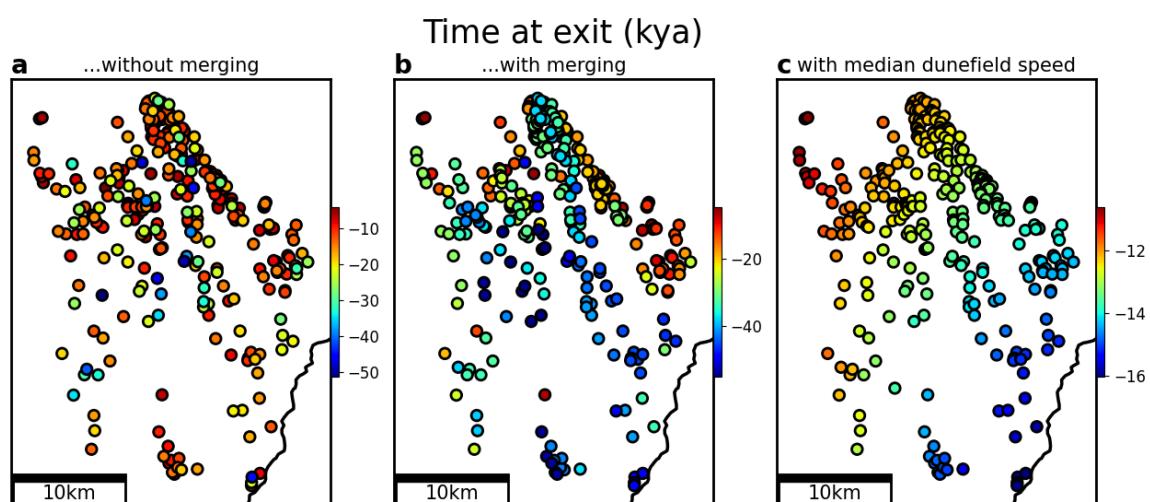


**Figure S2.** Feature histograms of the dune pairs, including: (a) their widths, (b) their migration rate (2003-2013), and (c) the comparison between their widths and migration rates showing anti-correlation. In panel c, the fitted empirical model fitted from about 60 dunes in Qatar (Michel et al., 2018) and used in this study to predict the migration rate from newly merged widths is shown.

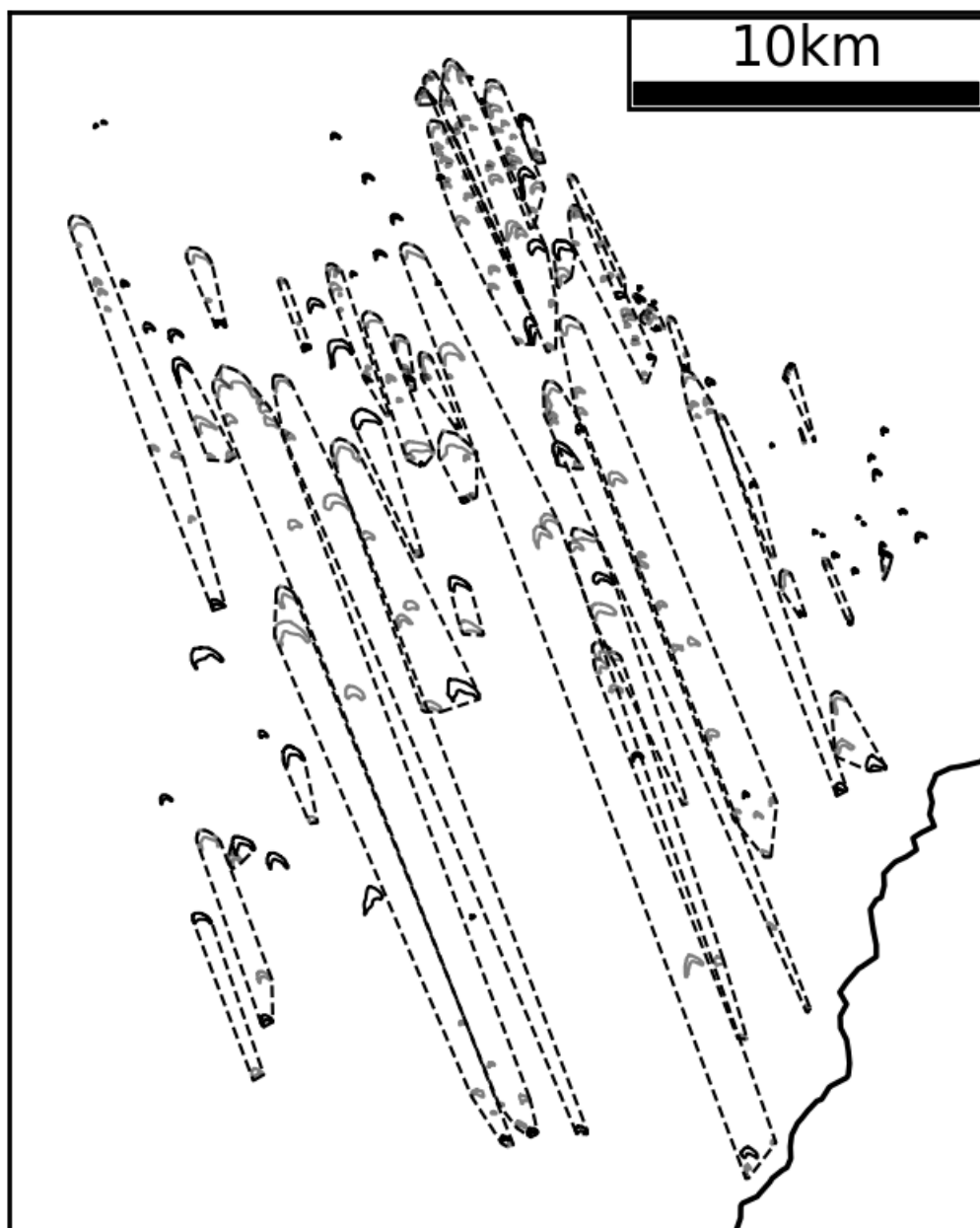


**Figure S3.** Spatial distribution of Size and volume of the dunefield. (a) Histogram of downfield dune distances starting from upwind to downwind. (b) Histogram of across-field dune distances starting from the western side of the southeastward migrating dunefield. Also, the mean velocity is displayed as a function of downfield distance in panel (a), and across-field distance in panel (b). (c) Histogram of downfield volume fractions. (d) Histogram of across-field volume fractions.

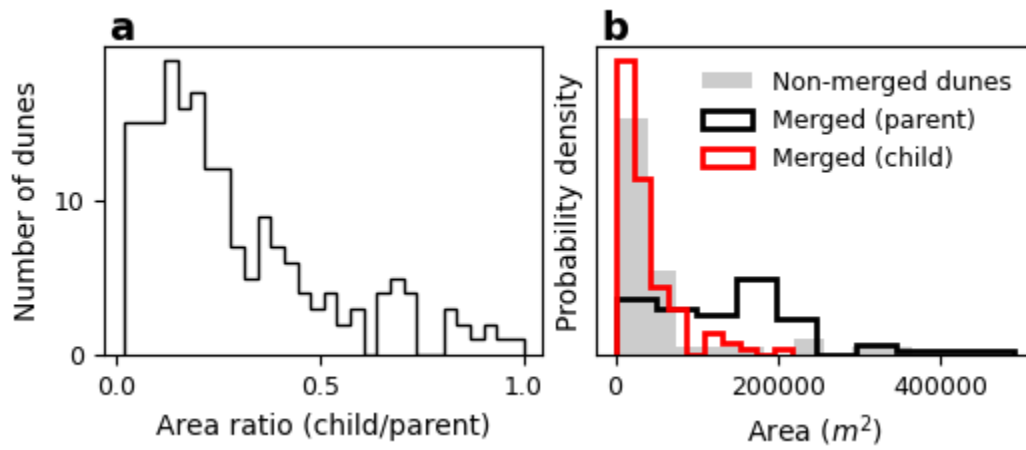




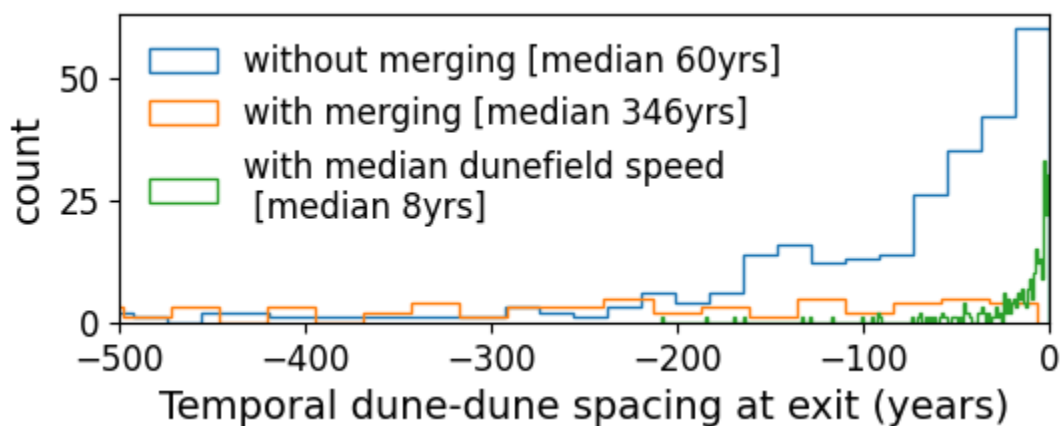
**Figure S4.** Maps of exit time of barchans of the three scenarios. Dunes positions reflect their locations in 2003, color-shaded with the time recorded when each dune left the northern coast.



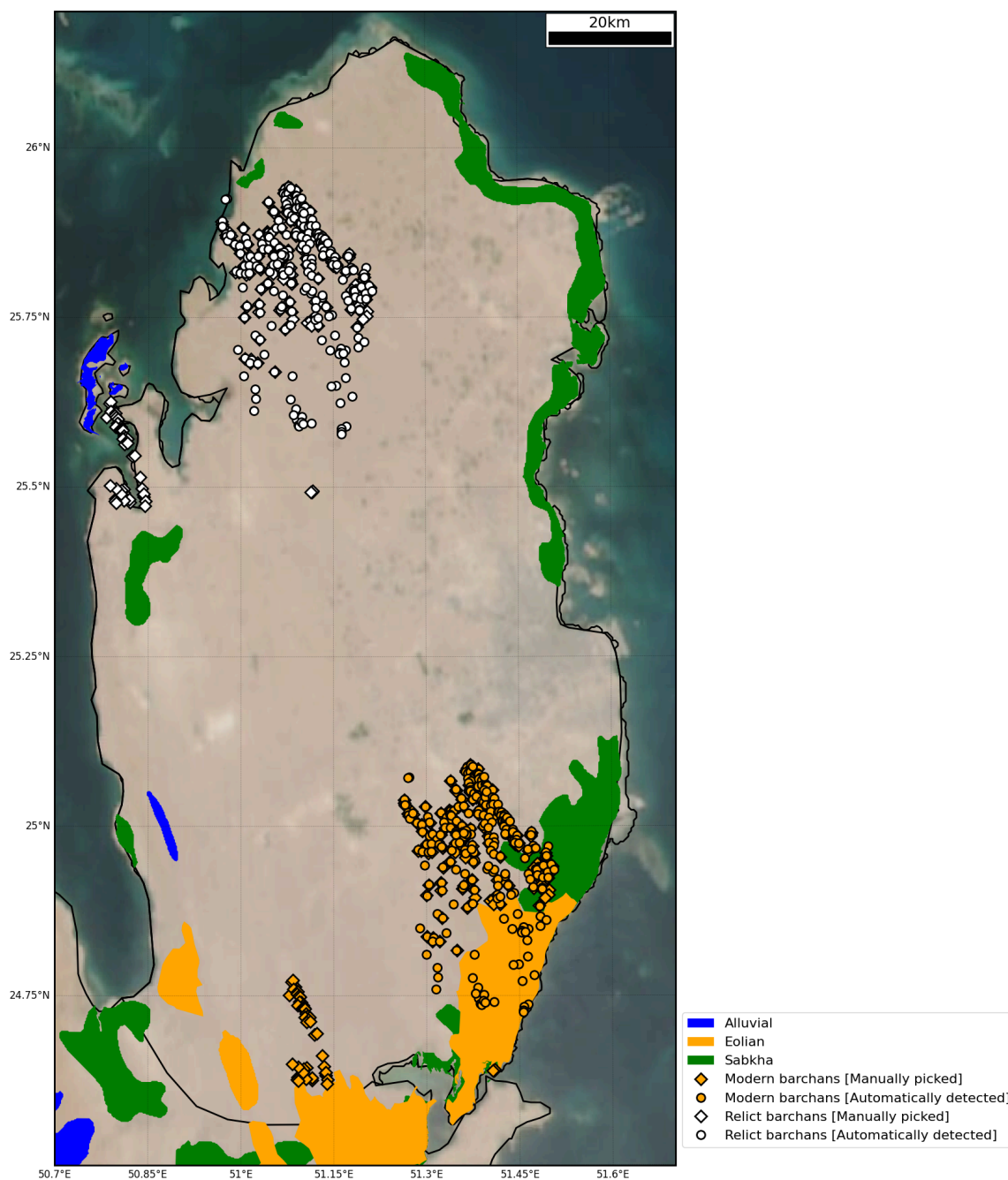
**Figure S5.** Grouping of dunes that merged in the second scenario. Note that the trajectories of many dunes were aligned all the way to the southern coast.



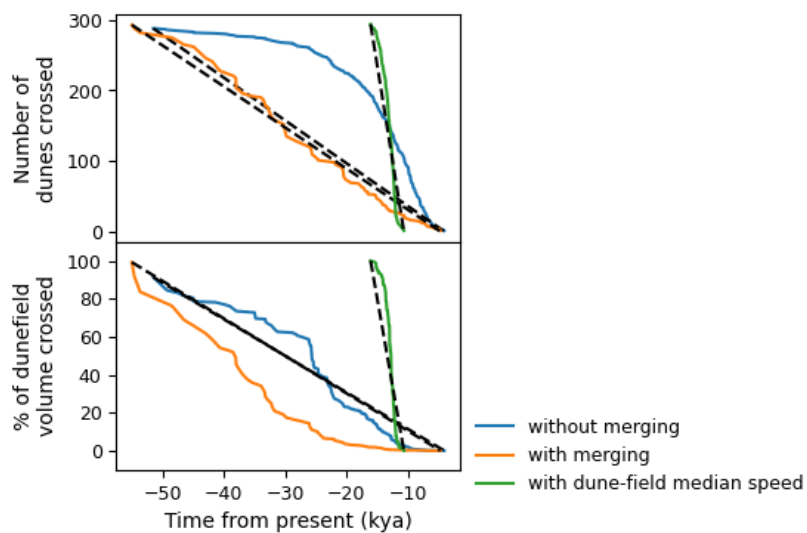
**Figure S6.** Statistics of the dunes that merged within 60k back in time. (a) The area ratios of the smaller dunes that merged to the larger dunes they merged into. (b) the probability density of dunes that did not merge with any other dune, dunes that merged with larger dunes, and dunes that other dunes merged into, normalized for comparison.



**Figure S7.** Exit time differences in the three scenarios. Median time spacing is also shown. The x-axis has been zoomed in for better visualization. The maximum time spacing is 3,655yrs for the first scenario (not displayed), 5,178yrs for the second scenario (not displayed), and 209yrs for the third scenario, where the uniform dunefield speed was set as the median speed.



**Figure S8.** Map of the Qatar peninsula, with all isolated barchans, in addition to Sabkhas and Eolian covers. Note: sabkhas were not extensive in the north as they were in the southern coasts, indicating limited variation in coastlines in the northern coastlines where the sand source was cut off.



**Figure S9.** Cumulative dune count and volume percentage that crossed the northern coast as dunes were back-propagated in the last 60ka BP.

## CHAPTER 6: CONCLUSIONS

In this thesis, I investigate surface processes in river deltas and barchan dune fields using remote sensing. I introduce in Chapter 1 that remote sensing of geomorphic change is vital for analyzing how river deltas build land to survive submersion due to sea-level rise, and at what rate barchan dunes migrate in aeolian dune fields to predict their sand mobility under different environmental conditions. I present repeat lidar differencing as a method for estimating accretion rates in subaerial deltaic lands, and an automatic segmentation and tracking workflow for measuring migration rates of barchan dunes.

I present in Chapter 2 the lidar differencing method for mapping accretion, covering several steps of ground filtering and co-registration. Next, using different spatial metrics (e.g., distance from delta apex, distance from island edges, ground elevation), I observe that accretion has dominant spatial patterns. These patterns reveal that regions near sediment sources at island edges and accessible to moderate inundation frequency (within the high-intertidal zone) are more resilient than other regions. I show that the dependence of accretion on inundation frequency and the downstream-steepening of floodwater gradients explain why the delta tends to maintain an equilibrium gradient. Moreover, island morphology and vegetation cause further variability of accretion in the delta. I also show that large flooding events add elevation surplus to deltaic lands in short time intervals and increase their trapping efficiency.

The consistent decay of accretion toward island interiors observed in Chapter 2 suggests that island interiors are most vulnerable to submersion. In Chapter 3, I show that sediment delivery by secondary channels can serve as a mechanism for bypassing levees and replenishing island interiors. I quantify how secondary channels can increase accretion rates in island interiors to levels comparable to those at levees, thereby helping the delta keep pace with relative sea-level rise beyond the island margins, even though secondary-channel lobes cover only a fraction of the total subaerial island area. I also show that these secondary channels cycle through initiation, progradation, and backfilling, consistent with predictions from numerical models. The cyclical behavior of secondary channels, combined with their tendency to fill the most sediment-starved topographic lows, suggests that they redistribute deposition across island interiors through time, promoting more spatially uniform island accretion through compensational stacking of channel lobes.

I next explore variability in dune morphology in the barchan dune field to relate it to changes in environmental conditions. In Chapter 4, I present an automated workflow that not only trains an instance segmentation model to detect and segment barchan dunes but also tracks these dunes to measure their migration rates. In a dune field in Qatar, I show that coastal barchan dunes have migration rates like those inland. The

expanded dataset of barchan migration rates reveals that the short interdune spacing in coastal lands is most likely not caused by modern stabilization, but rather by an ancient marine transgression more than 1ka BP that left a relict dune field. In the future, I will attempt to extract all crestlines of other dune morphologies and check if they have similar migration rates as barchan dunes. Also, it would be worth investigating larger datasets of dune migration in other regions since a good workflow is achieved. We anticipate that studies that automatically detect and track dunes might encounter the same obstacles we faced, which we attempted to remedy. Using the outlines of dune contours rather than their centroids is shown to improve displacement measurement accuracy.

In Chapter 5, I use migration rates measured in Qatar to backpropagate dunes back in time to the northern coasts and show that the arrival time of these dunes coincides with the timing of Arabo-Persian Gulf filling, which cut off the aeolian sand source in Qatar and east Arabia. I also show that these dunes can be traced back to the paleo-rivers in the Gulf, which were fed by the Zagros Orogeny, rather than from Arabia.



