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UNIVERSITY OF CALIFORNIA SAN DIEGO

From Subsurface to Shoreline:
Impacts of Sea Level Rise on Coastal Groundwater, Reef Dissipation, and Beach
Morphology

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy

in

Oceanography

by

Austin T. Barnes

Committee in charge:

Mark A. Merrifield, Chair
Janet M. Becker
Charles H. Fletcher
Katharine L. Ricke
Adam P. Young

2025

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University of California San Diego

2025

DEDICATION

This dissertation is dedicated to the communities and individuals whose existences, livelihoods, and homes are threatened by the climate crisis — a crisis driven largely by an extractive, profit-driven system that devalues people and our planet. It is my hope that I can use the privilege of my position to increase mindfulness of the global emergency we face and of the communities bearing the brunt of its impact, no matter how far they may be from our own doorsteps.

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ACKNOWLEDGEMENTS

Chapter 1, in full, has been submitted for publication of the material as it may appear in Earth's Future. Barnes, Austin T.; Merrifield, Mark A.; Bagheri, Kian; Levy, Morgan C.; Davani, Hassan, American Geophysical Union. The dissertation author was the primary investigator and author of this paper.

Chapter 2, in full, is a reprint of the material as it appears in Scientific Reports 2024. Barnes, Austin T.; Becker, Janet M.; Tagarino, Kelley A.; O'Reilly, William C.; Siegelman, Mika; Thompson, Philip R.; Merrifield, Mark A., Springer Nature, 2024. The dissertation author was the primary investigator and author of this paper.

Chapter 3, in full, is currently being prepared for submission for publication of the material. Barnes, Austin T.; Merrifield, Mark A.; O'Reilly, William C.; Mikkelsen, Anna B.; Moskvichev, Richelle U. The dissertation author was the primary investigator and author of this material.

Thank you to my advisor and friend, Mark Merrifield, for taking me on for this apprenticeship. Thank you, Mark and Janet, for taking me in and providing your guidance both at UHM and here at SIO.

Thank you Bill, Michele, Adam, the rest of the Coastal Processes Group, Kate for serving on my committee, and Chip for not only serving on my committee but also welcoming me into your group at UHM, I hope to keep working with you all.

Mahalo nunui to Mymai, Myfamily, and Myfriends for helping me make it through this. This is really the work of all of you, my home, and my community, through me.

VITA

2025 Doctor of Philosophy, University of California San Diego

FIELDS OF STUDY

Major Field: Oceanography

ABSTRACT OF THE DISSERTATION

From Subsurface to Shoreline:
Impacts of Sea Level Rise on Coastal Groundwater, Reef Dissipation, and Beach
Morphology

by

Austin T. Barnes

Doctor of Philosophy in Oceanography

University of California San Diego, 2025

Mark A. Merrifield, Chair

Coastal systems face unprecedented challenges from sea level rise (SLR), threatening natural mechanisms that dissipate ocean wave energy and regulate shoreline stability. This dissertation integrates three critical lines of investigation to assess how SLR disrupts coastal protection systems across spatial and temporal scales. First, groundwater observation and modeling reveals that sea level rise is projected to exacerbate coastal flooding through subsurface emergence in Imperial Beach, California by the end of the century. Second, hydrodynamic analysis of a reef in American Samoa demonstrates that SLR reduces reef dissipation of nearshore sea-swell wave energy. If reefs are unable to dissipate incident

sea-swell energy due to SLR, places like American Samoa will need to prepare for dramatic increases in wave run-up and nearshore wave forces. Third, satellite-derived shoreline analyses of O‘ahu, Hawai‘i, demonstrate that interannual sea level variability drives interannual beach width change for many of O‘ahu’s beaches. The increased shoreline sea-swell variability due to SLR modeled in American Samoa may drive increases in sandy beach shoreline erosion around many shorelines of O‘ahu. These findings collectively highlight the need for adaptive strategies that address groundwater flooding, reef degradation, and sediment dynamics as interconnected components of coastal resilience.

Introduction

Our coastlines are amazing, complex systems that include intricate mechanisms capable of dissipating the potentially harmful effects of sea level oscillations over a range of temporal scales – from individual waves running up the beach to multi-decadal variability. These natural defenses provide protection from extreme water levels and wave energy, but accelerating global sea level rise (SLR) threatens to overwhelm some of these natural defenses. Studies are demonstrating how SLR will worsen passive flooding (Thompson et al. 2021), coastal erosion (Vitousek et al. 2017), wave inundation (Anderson et al. 2018), and groundwater rise (Habel et al. 2024). This dissertation examines three critical yet vulnerable coastal features that mediate sea level impacts: groundwater systems, fringing reefs, and sandy beaches. Through analyses spanning empirical groundwater studies, hydrodynamic modeling, and satellite remote sensing, these chapters reveal how SLR alters fundamental coastal processes, with cascading consequences for flooding, erosion, and community resilience.

Groundwater in coastal areas is often closely linked to the ocean. SLR is rapidly increasing risks associated with groundwater such as buried infrastructure infiltration (Bjerklie et al. 2012), flooding due to emergence (Rotzoll and Fletcher 2013) or compounding effects (Rahimi et al. 2020), increased salinity (Adams et al. 2024), and contaminant mobilization (McKenzie et al. 2021). Groundwater table modeling in California has taken a crucial first step in identifying high risk areas particularly vulnerable to SLR effects on the coastal aquifer (Befus et al. 2020), but direct research on sea level-driven groundwater variability remains limited. In Chapter 1, I present results from an observational and

dynamic modeling study of the shallow, unconfined coastal aquifer of Imperial Beach, California. We find that the sandy soil along the coastline is highly transmissive of the diurnal and semidiurnal ocean tides and lower frequency sea level variability. We create projections for the aquifer underlying the coastal roadway with regional SLR scenarios to show that groundwater emergence will become a frequent flooding hazard by 2100, with emergence likely in the coming decades. Over 20% of San Diego’s coastline shares a similar transmissive sandy geology and therefore a similar flooding risk, emphasizing the importance of local groundwater table observation and modeling.

In Chapter 2, I present a study of how SLR is leading to important increases in nearshore wave energy at a fringing reef in American Samoa with implications for other reef-fringed shorelines. American Samoa continues to experience land subsidence from a series of large earthquakes in 2009 (Han et al. 2019) resulting in rapid relative sea level rise for the main island of Tutuila (Widlansky et al. 2017). Tutuila is sheltered from energetic wave events by a broad (up to 600m), shallow (<2 m) fringing reef surrounding most of the island. Multiple studies have demonstrated the protective nature of fringing reefs, especially from incident sea-swell wave energy (Ferrario et al. 2014; Becker et al. 2014). Shallow reefs cause depth-limited breaking of sea-swell waves at the outer reef crests or on the reef flats, and additional wave energy dissipation due to friction (Lowe et al. 2005; Monismith et al. 2015). I report observational findings at a single Tutuila reef in Faga’itua Bay indicating that nearshore sea-swell wave heights are controlled by water level over the reef, and extrapolate that relationship to higher sea levels using a one-dimensional, phase-resolving nonhydrostatic wave model. I show that if the coral growth on the fringing reef is unable to counter SLR, increases in reef flat water level result in increased transmission of sea and swell energy to the shoreline. This diminished protection has direct implications for adjacent shorelines, as reefs can no longer mitigate wave-induced flooding and wave impacts on coastal protection structures.

The implications of Chapter 2 motivate and inform our findings from Chapter 3,

in which I show that many sandy shorelines around the island of O‘ahu, Hawai‘i exhibit strong sensitivity to interannual sea level variability. I use the satellite-derived shoreline position data from Moskvichev et al. (2025) to investigate potential drivers of interannual beach width changes. Changes from year to year, occurring at timescales between seasonal and decadal, have not been well studied along much of O‘ahu, Hawai‘i, despite their management implications. Understanding these interannual variations and their drivers will provide crucial links between subannual processes and decadal trends so that we may better anticipate future shoreline change. Many of these shorelines are fronted by coral reefs sharing some similarities with Faga‘itua Bay in American Samoa; analogous effects of water level on nearshore wave energy have been observed (Inman et al. 1964; Lowe et al. 2009). I find that nearly half of studied littoral cells on O‘ahu experience erosion and accretion patterns tied to annual sea level anomalies. The shorelines with the greatest reef protection show responses linked to reef platform geometry, and I hypothesize that higher water levels amplify cross-shore and alongshore sediment transport mechanisms with important implications for future SLR.

Together, these studies underscore interconnected vulnerabilities across coastal systems. Sea level variability drives groundwater inundation that compromises infrastructure stability from below and can cause or compound flooding. Sea level also controls the capacity of fringing reefs to dissipate offshore energy with direct implications for beach width. Managing these cascading impacts requires understanding of subsurface processes, reef hydrodynamics, and sediment pathways, all explored in this dissertation.

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Section: Journal of Applied Meteorology and Climatology.

Chapter 1

Flooding Projections due to Groundwater Emergence Caused by Sea Level Variability

1.1 Introduction

1.1.1 Coastal Groundwater and Sea Level Rise

Coastal areas are at increased risk of a range of natural hazards as sea levels rise. Many studies have established and projected the effects of sea level rise (SLR) on passive flooding (e.g., Thompson et al. 2021), coastal erosion (e.g., Bruun 1962; Day 2004; Vitousek et al. 2017), and wave inundation (e.g., Anderson et al. 2018; Vitousek et al. 2017). Recently, more attention is being paid to the threat of rising groundwater levels (Barnard et al. 2024; Thomas et al. 2024; Cox et al. 2025) in association with SLR (Habel et al. 2024). Specifically, coastal groundwater rise can accompany SLR, and push the interface between saline and fresh water farther inland (Jiao and Post 2019). Thus, SLR can increase the salinity of fresh coastal aquifers used for drinking and agriculture (Adams et al. 2024; Anderson and Al-Thani 2016), infiltrate buried infrastructure (Bjerklie et al. 2012), drive flooding through emergence (Rotzoll and Fletcher 2013), and exacerbate compound flooding when combinations of storm surge, high tides, rainfall, elevated river flows, and shallow or emergent groundwater tables occur (Rahimi et al. 2020). Furthermore, rising

groundwater tables can mobilize soil contaminants and increase wastewater leakage, leading to serious human health impacts (Hill et al. 2023; McKenzie et al. 2021). Importantly, high-resolution empirical frameworks can reveal early flooding risks from groundwater shoaling even before direct coastal inundation, emphasizing the need to integrate observed groundwater dynamics with topography and hydrogeology when assessing SLR-driven risks (Cox et al. 2025).

Sea level-driven variability in groundwater table elevations (GWT) in coastal California has not been extensively studied apart from SLR modeling. This is a key knowledge gap that this study aims to address. Groundwater modeling studies help elucidate the potential hazards of rising groundwater levels but are limited by the availability of direct geological and groundwater observations, especially near the coastline where groundwater is understudied because it is typically unsuitable for agriculture or drinking water. Many modeling studies simulate groundwater interactions with SLR by assuming a “flux-controlled” mode in which GWT rise linearly with ocean levels (Hoover et al. 2017; Rotzoll and Fletcher 2013). Hoover et al. (2017) carried out one of the earliest studies of SLR impacts on groundwater emergence and shoaling in coastal California, focusing on three sites (Arcata, Stinson Beach, and Malibu Lagoon). Their study calculated GWT relative to digital elevation models of surface topography at 1 m and 2 m of SLR using constructed groundwater surfaces, highlighting SLR-driven groundwater vulnerabilities. However, this “flux-controlled” method ignores drainage features of the local landscape that will decrease groundwater rise (Befus et al. 2020; Michael et al. 2013). In the most comprehensive groundwater study of coastal California performed to date, Befus et al. (2020) found that using local topography to allow for groundwater drainage decreases the extent of groundwater rise in a majority of California’s coastal aquifers. They used homogeneous, steady-state simulations of the unconfined GWT using MODFLOW, a popular open-source 3D numerical groundwater model (McDonald and Harbaugh 1984), across a range of SLR increments, identifying areas of shallow and emergent water tables

and other potential vulnerabilities. Their study highlights the importance of using local topography for groundwater modeling and sets the stage for regional studies to incorporate local geology and dynamic behavior of coastal aquifers for future SLR adaptation.

The local geology of coastal aquifers determines important properties that affect how the aquifer responds to forcings like precipitation and ocean tides. For idealized, semi-infinite, unconfined, homogeneous and isotropic aquifers, hydrologic properties including specific yield, porosity, and hydraulic conductivity influence aquifer storage and drainage. Hydraulic diffusivity, which is the ratio of transmissivity to specific yield, determines how dynamic boundary conditions like ocean tides propagate through the aquifer as a function of the tidal amplitude, period, and distance from the coastline (Ferris 1952; Jacob 1950). Highly transmissive media like sandy dune deposits or aquifers with networks of cracks and voids like fossil reefs and karst landscapes can transmit ocean tidal signals kilometers inland (Rotzoll et al. 2013; Rotzoll and El-Kadi 2008). Befus et al. (2020) did not incorporate local geology into their simulations but covered a range of possibilities by modeling three different hydraulic conductivities of 0.1, 1, and 10 m/day. Additionally, to give a sense of groundwater variability due to ocean tides, Befus et al. (2020) bracketed groundwater response using both local mean sea level (LMSL) and mean higher high water (MHHW) as static ocean boundary conditions. Direct groundwater observations in a variety of geological settings are necessary for generalized models to be capable of assisting local stakeholders in SLR adaptation planning.

1.1.2 Case Study: Imperial Beach, California

We focus our study on Imperial Beach, California, part of the Befus et al. (2020) model domain, to assess their statewide modeling at a regional scale, determine the primary drivers of groundwater variability, and refine estimates of SLR impacts. Imperial Beach is the southernmost coastal city of California, situated just north of the U.S.-Mexico border. It is surrounded by the Pacific Ocean to the west, San Diego Bay to the north, and the

Tijuana River Estuary to the south. Much of the city lies within several meters elevation of MHHW, putting it at high risk of compound flooding events. Imperial Beach already experiences flooding from combinations of high tides, large ocean waves, and rainfall several times a year (Gallien 2016; Merrifield et al. 2021). Parts of the city up to 2 km away from the Pacific coastline but close to the other tidally-linked bodies of water have been observed to flood at high tide (Revell Coastal 2016), motivating further investigations into the ocean’s influence throughout the city.

Results from a preliminary study of Imperial Beach’s vulnerability to SLR (Revell Coastal 2016) led to the development of a community resilience plan for monitoring and adaptation (City of Imperial Beach 2024), but the impacts of shallow and emergent groundwater are not integrated in this version of the plan. The 2016 SLR vulnerability assessment analyzed hazards from a 100-year wave event, coastal erosion, tidal inundation, and nuisance stormwater flooding; the community resilience plan includes corresponding detailed adaptation and mitigation strategies. However, these efforts may prove inadequate if emergence of shallow groundwater follows a similar timeline as these other flood risks.

Two studies were conducted using time-averaged groundwater observations to model the impacts of SLR and precipitation events on Imperial Beach’s storm drainage (Sangsefidi et al. 2023a) and sewage infrastructure (Sangsefidi et al. 2023b). Sangsefidi et al. (2023a) used the static groundwater model of Befus et al. (2020) to develop a stormwater model and estimate coastal storm drain vulnerability to seawater, groundwater, and stormwater flooding. Sangsefidi et al. (2023b) extended that work by developing a site-specific static groundwater model of Imperial Beach to investigate climate change impacts on sanitary sewer infrastructure. These studies present results at increments of SLR under several modeled rainfall events without considering tidal variability or future changes in precipitation and soil evapotranspiration.

Building from this prior research, the main goal of this study is to use direct GWT observations to better understand drivers of GWT variation including ocean tides and to

estimate the impacts of SLR on groundwater levels under a changing climate in Imperial Beach. Understanding of groundwater behavior and projected effects of SLR from Imperial Beach is directly relevant to understanding in other parts of the Southern California’s coastline with similar geologies and can inform development in low-lying coastal regions broadly. GWT fluctuations from changes in ocean water levels over a range of time scales have been observed in similar, nearby California beaches, and in barrier islands with comparable geometries. At Torrey Pines Beach, less than 40 km north of Imperial Beach, significant spring-neap fluctuations of the beach GWT were observed 100 m from the mean shoreline location, despite attenuation of the diurnal and semi-diurnal tides (Raubenheimer et al. 1998, 1999). Groundwater observations in a 550 m-wide barrier island in the Outer Banks, North Carolina, revealed diurnal and semi-diurnal tidal fluctuations (Housego et al. 2023) and previously underpredicted increases in groundwater heads due to storm surge and wave setup (Housego et al. 2021).

We develop a dynamic, empirical groundwater model based on local time series measurements to project groundwater emergence with SLR. While numerical groundwater models like MODFLOW are useful for estimating groundwater surfaces over large spatial extents, 1D time series analysis models can provide insight into drivers of groundwater variability at a single location, and can achieve better agreement with observations at that location (Bakker and Schaars 2019). For this study, we use the open source time series analysis tool Pastas (Collenteur et al. 2019), with which we simulate groundwater level variability with a transfer function-noise (TFN) approach, wherein statistical functions are used to translate time series inputs (e.g., precipitation and evapotranspiration) into outputs (e.g., groundwater levels). Pastas has been used in a variety of geological settings to characterize soil moisture dynamics (Pezij et al. 2020) and estimate groundwater recharge (Collenteur et al. 2021). Similar to this study, the relative influence of recharge, storm-surge, tides, and waves on groundwater levels and salinization were assessed using Pastas at three barrier island sites on the U.S. Atlantic coast (Frederiks et al. 2024). Thus,

we use Pastas to analyze and model groundwater level variation at the coast in Imperial Beach during a historical (hindcast and observed) period of 2003-2024. Using that model, we project future (2024-2100) groundwater rise using scenarios from the regional U.S. Sea Level Rise and Coastal Flood Hazard Scenarios and Tools Interagency Task Force (Sweet et al. 2022) and dynamically downscaled World Climate Research Programme Coupled Model Intercomparison Project 6 (CMIP6) (Rahimi et al. 2024). We use our groundwater level projections between 2024-2100 to produce annual flooding metrics under five SLR scenarios for multiple locations along the coastline of Imperial Beach.

Methods including the collection of groundwater well measurements; model data inputs; modeling approach, parameterization, and validation; the generation of hindcasts and projections; and development of flood metrics are detailed in Section 1.2. Results from the analysis of groundwater observations, including comparisons to Befus et al. (2020), and the analysis of groundwater and flood metric projections are described in Section 1.3. Discussion of and conclusions drawn from the analysis of observations and model projections for the City of Imperial Beach are presented in Section 1.4.

1.2 Data and Methods

1.2.1 Groundwater Wells and Water Table Measurements

In December 2021, we installed four groundwater monitoring wells in Imperial Beach, California (Figure 1.1). Locations of the wells are in or near frequently flooded areas identified by the city government. All wells were installed in the unconfined surface aquifer to a depth of 6 m using an 0.2 m diameter well boring. The 0.05 m diameter PVC well casing contained 0.0005 m screening along the bottom 3 m of casing; the top 3 m contained no permeable screening. The wells were backfilled with sand, capped with an annular bentonite seal, and sealed with traffic grade surface concrete and a waterproof well vault and cover following San Diego County standards. All wells extended more than

1.5 m below the water table during data collection.

We classified soil samples acquired from drilling during well installation using a gradation test (ASTM International 2011), and we made estimates of hydraulic conductivity using HydrogeoSieveXL (Devlin 2015); classifications and estimates varied by location and depth (see text S1 and figures S1-S4 in Barnes_SupplementalS1.pdf). While informative, the hydraulic conductivity estimates may not be entirely representative of aquifer properties because the test method employed here is not ideal for the dense clays found at groundwater monitoring wells 2, 3, and 4. Geological maps from the United States Department of Agriculture (USDA) Web Soil Survey indicate two distinct surface geologies for Imperial Beach (Figure 1.1). Along the coast, there are coarse sandy dune deposits that are relatively transmissive, including along all of Seacoast Drive. Alternately, less than a kilometer from the ocean, dense clay/sand estuarine deposit mixtures with relatively low hydraulic conductivity and low transmissivity exist throughout most of the city where the San Diego Bay and estuary were once linked (Soil Survey Staff). For more information on the geology, groundwater and surface water interactions of the Tijuana River Estuary, see Stuart (2008) and the 2016 City of Imperial Beach Sea Level Rise Assessment (Revell Coastal 2016).

We collected time series of GWT relative to a fixed vertical datum and local land surface elevation from 8 December 2021 through 14 May 2024 (data available in Barnes et al. 2025). In each groundwater monitoring well, a single unvented pressure sensor (RBR Solo) was attached to Kevlar line and submerged ~ 1 m below the GWT. From 8 December 2021 through 21 November 2023, total pressure was recorded at 1 Hz; from 22 November 2023 through 14 May 2024, sampling occurred at 0.1 Hz. Gaps in sampling are a result of battery failures leading to data loss. We estimate negligible barometric efficiency factors for each of the wells (Jacob 1950); therefore, to estimate hydrostatic pressure from total pressure measurements, p_{total} , we subtracted atmospheric pressure measurements, p_{atm} , that were collected every 6 min from NOAA’s National Data Buoy Center (NDBC)

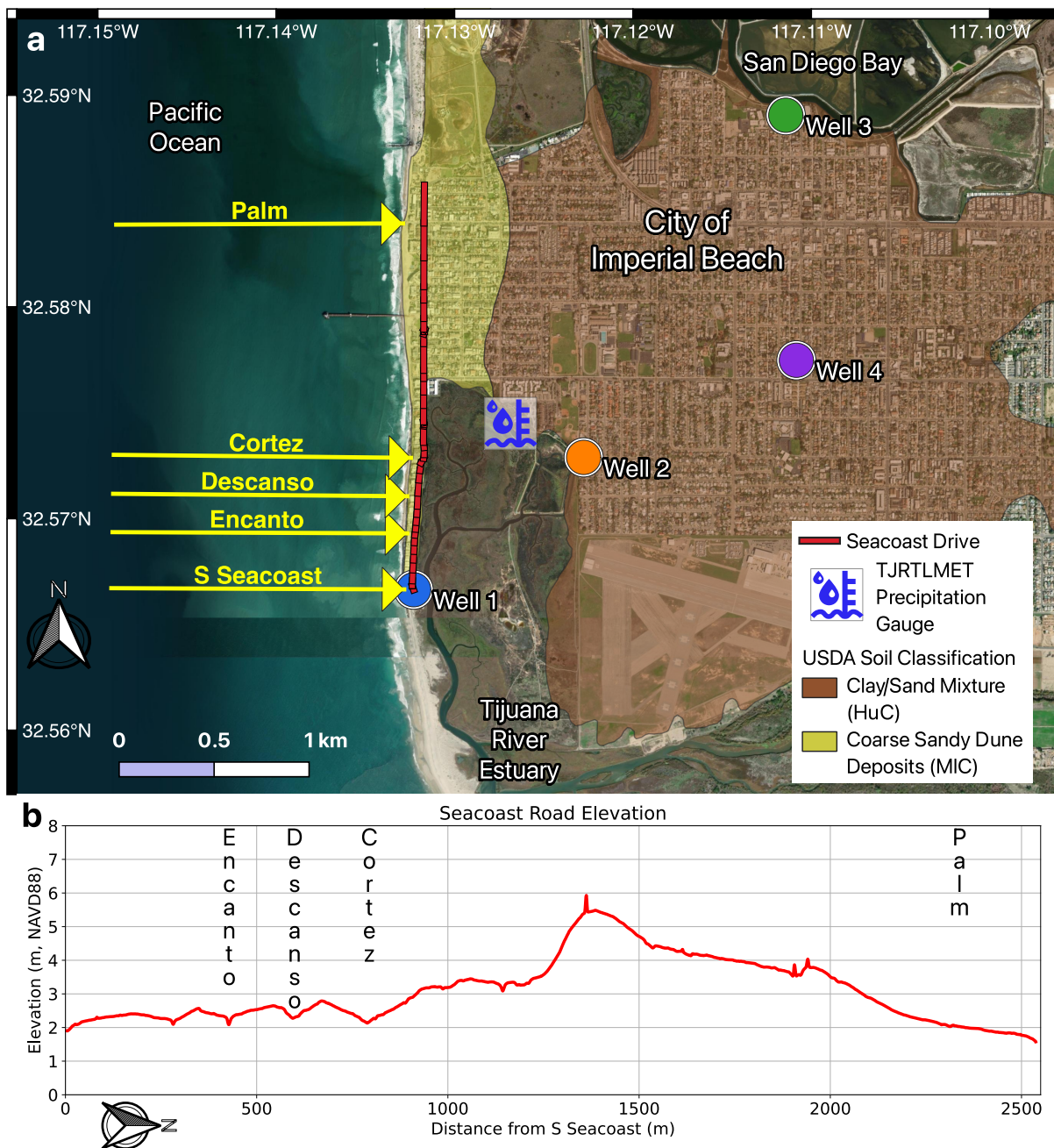


Figure 1.1. (a) Map of Imperial Beach, California, including the locations of 4 groundwater monitoring wells used in this study (basemap from ESRI, 2017). Locations of low-lying cross-street intersections along Seacoast Drive are indicated with yellow arrows. (b) Road surface elevation along Seacoast Drive from Young et al. (2018), including corresponding cross-street intersections.

station SDBC1-9410170 at the San Diego airport and linearly interpolated to match sensor samples. Hydrostatic pressure is converted to sensor depth below the water table, h_{sensor} :

$$h_{sensor}(t) = \frac{p_{total}(t) - p_{atm}(t)}{\rho g} \quad (1.1)$$

We determined an average well water density, ρ , using intermittent vertical profiles of conductivity-temperature-depth (CTD) and the TEOS-10 conversion (see text S2 in Barnes_SupplementalS1.pdf Roquet et al. 2015): $\rho_1 = 1014.4 \text{ kg/m}^3$, $\rho_2 = 999.1 \text{ kg/m}^3$, $\rho_3 = 1001.0 \text{ kg/m}^3$, and $\rho_4 = 998.8 \text{ kg/m}^3$; $g = 9.81 \text{ m/s}^2$ is the acceleration due to gravity. We determine GWT time series relative to the North American Vertical Datum of 1988, h_{NAVD88} , by referencing the depth of the sensor at the beginning of each data collection period, $h_{sensor}(t_0)$, to manual static measurements of depth to water table, $h_{wt,NAVD88}(t_0)$, relative to a GPS-surveyed point at the top of the well:

$$h_{NAVD88}(t) = h_{sensor}(t_0) - h_{wt,NAVD88}(t_0) + h_{sensor}(t) \quad (1.2)$$

GWT relative to the local land surface, hereafter referred to as depth to water table, d_{wt} , are computed by subtracting the land surface elevation at the well location, z_{surf} , from the GWT time series, both referenced to the same datum:

$$d_{wt}(t) = h_{NAVD88}(t) - z_{surf} \quad (1.3)$$

A negative depth to water table indicates the water table is below the land surface, true of all observations from this study.

We estimate a maximum of 0.03 m of total uncertainty in both GWT and depth to water table measurements by combining independent GPS elevation, manual static measurement, and pressure sensor drift uncertainties. Combined standard uncertainty was calculated using the root-sum-square method, assuming no correlation between uncertainty

components (Taylor and Kuyatt 1994). GPS surveyed elevations are constrained to less than 0.01 m error, and the manual static measurements are constrained within 0.005 m. Error from pressure sensor drift is ≤ 0.02 m. The well water density standard deviations as a result of temperature and salinity fluctuations are $\sigma_1 = 4 \text{ kg/m}^3$, and $\sigma_{2,3,4} \leq 1 \text{ kg/m}^3$; these density fluctuations contribute negligible uncertainty relative to other sources of error.

1.2.2 Model Data Inputs

Model input time series include reconstructed hourly predictions of the La Jolla tide, non-tidal sea level at the La Jolla tide gauge, precipitation, and reference evapotranspiration (ET_0 or ET_{ref}). We derived hourly time series of the La Jolla tide from the La Jolla tide gauge (NOAA CO-OPS station 9410230) hourly water levels. The La Jolla tide gauge provides good estimates ($r = 0.998$, root mean square error = 0.03 m) of Imperial Beach water levels with no apparent time difference (Merrifield et al. 2021). We reconstructed hourly predictions of the La Jolla tide using the open-source Python package UTide v1.0 (Codiga 2011) to determine amplitudes and phases of the tidal harmonic constituents from NOAA’s current tidal datum analysis period 1 January 1983 to 31 December 2001. UTide constituent amplitudes and phases determined using ordinary least squares match the harmonic constituents published by NOAA. We did not include a linear sea level trend in the tide component. We employed the nodal mode to enable accurate nodal and satellite corrections for tidal constituents, accounting for subtle but important multi-year astronomical variations in tidal forcing, including the 4.4- and 18.61-year lunar nodal cycles (Codiga 2011). We used the ‘auto’ setting and conventional Rayleigh criterion, $R_{min} > 1$, to filter for independent tidal constituents. Because the reported amplitudes of the solar semiannual (SSA) and annual (SA) constituents include both tidal and seasonal thermal and wind-driven fluctuations in the sea surface, we set these amplitudes in our UTide reconstruction to 0 so that variations at these frequencies are captured in the non-tidal

sea level and not double counted.

We estimated the non-tidal residual sea level (NTR) at the La Jolla tide gauge by subtracting the UTide tidal reconstruction from the observed hourly water levels before applying a cosine-Lanczos squared filter with a cutoff of 36 hours, chosen because it effectively filters diurnal tidal signals while minimizing attenuation of 2–3-day periodic variability (Walters and Heston 1982). In the historical data, NTR includes sea level trends. For model projections from 1 October 2024 to 30 September 2100, we generated 25 realizations of hourly NTR using historical observations from 1 October 1926 to 30 September 2024. We removed the linear trend representing SLR from the historical water level observations due to our subsequent inclusion of projected SLR (see below). Gaps in historical NTR less than or equal to 1 month were linearly interpolated and years with gaps greater than 1 month were excluded, yielding 87 years of historical annual NTR. NTR anomalies are highest during summer (+9 cm) and lowest in winter (-9 cm), with a standard deviation for any given day between 5 and 10 cm. We synthesized NTR time series using random draws of annual integral blocks. We prioritize preserving autocorrelation over creating an inferred distribution with unobserved extrema. This method allows for statistics to be drawn from observation-driven synthetic time series under the assumption that NTR will not change significantly this century. The 87-year record includes 9 major El Niño events when NTR anomalies reached +20-40 cm in late fall/early winter.

We combined our NTR ensemble with each of the five SLR scenarios developed by the Sea Level Rise Interagency Task Force (Sweet et al. 2022) to generate sea level projections that include non-tidal sea level variability. The projected sea levels include future SLR trends, which replace the historical trends removed from our estimated NTR (see above). For each of the SLR scenarios, Sweet et al. (2022) provide the 17th, 50th, and 83rd percentile of LMSL projections at the La Jolla Tide Gauge every decade from 2020 through 2150, relative to the 2000 annual average LMSL. We interpolated the decadal LMSL values to hourly resolution using the cubic spline interpolant from SciPy (Virtanen

et al. 2020).

For model parameterization, validation, and hindcasts, we acquired precipitation time series from the Tijuana River National Estuarine Research Reserve station TJRTLMET (NERRS) and spatially modeled ET_0 estimates from the California Irrigation Management Information System (CIMIS). TJRTLMET is located 1 km from well 1. We summed the TJRTLMET 15-minute daily precipitation observations, available starting 1 July 2001, to achieve hourly resolution. CIMIS ET_0 estimates are available at daily resolution with 2 km spatial resolution beginning 20 February 2003 (Hart et al. 2009). We obtained ET_0 from the grid cell containing well 1. We created a uniformly distributed hourly time series by assigning each hour the same value, calculated as the daily total divided by 24.

For projections of precipitation and evapotranspiration, we used 8 CMIP6 global climate model outputs from the relatively high-emissions scenario SSP3-7.0 that were dynamically downscaled using the Weather Research and Forecasting model (WRF) to a 3 km resolution for California (Rahimi et al. 2024). The 8 models include CESM2, CNRM-ESM2-1, EC-Earth3, EC-Earth3-Veg, FGOALS-g3, MIROC6, MPI-ESM1-2-HR, TaiESM1, and one individual variant per model (Rahimi et al. 2024). The 8 selected models are those that are understood to perform well over California, and that have been made publicly accessible in association with the California 5th Climate Change Assessment (Kalansky et al. 2023). The CMIP6 SSP3-7.0 scenario runs allow for exploration of climate variability over a sufficiently wide range of global average radiative forcing, temperature changes, land use changes, and near-term climate forcing (O'Neill et al. 2016). We used CMIP6-modeled daily precipitation and evapotranspiration (ET) from the grid cell containing well 1. We created a uniformly distributed hourly time series by assigning each hour the same value, calculated as the daily total divided by 24. We converted each climate model ET time series to ET_0 using scaling factors that result in the greatest r^2 correlation between scaled climate model ET from 1 October 2014 through 30 September 2024 and CIMIS

ET_0 estimates from the same period. The scaling factor functions similarly to a static crop coefficient, which is widely used to convert potential to actual evapotranspiration (George H. Hargreaves 1974). The scaling factors range from 3.4 to 9.0. We perform an additional mean bias correction to the projected GWT by subtracting the difference between the means of the hindcast recharge and the projected recharge. See text S3 in Barnes_SupplementalS1.pdf for additional details.

1.2.3 Modeling Approach, Parameterization, and Validation

We conducted groundwater modeling only at the well 1 (S Seacoast) location based on analysis of groundwater observations at all wells (Section 1.3.1). There is precedent to use a single well sensor to infer important aquifer properties (Le Mesnil et al. 2024). Based on the static groundwater models of Befus et al. (2020) and Sangsefidi et al. (2023b) for current and future sea levels with all modeled hydraulic conductivities, we believe the GWT at S Seacoast is representative of the entirety of Seacoast Drive. Away from the estuary (e.g., Palm Avenue), this assumption should be considered with caution because the influence of the Tijuana Estuary on the GWT along the southern Seacoast Drive peninsula is not fully understood.

We used the open-source Python package Pastas v1.5 (Collenteur et al. 2019) to create the empirical groundwater model. The Pastas model TFN approach convolves physically based, statistical impulse response functions with input time series and uses least squares fitting of free parameters to minimize error in the prediction of a target time series. The impulse response functions describe how the target time series responds to an input time series, and can take different functional forms (e.g., exponential or Gamma distribution functions). The exponential and Gamma functions describe immediate and delayed responses, respectively, that decay exponentially. Our target time series is the hourly average GWT time series. Input time series, referred to as stress models in the Pastas framework, include reconstructed hourly predictions of the La Jolla tide, non-tidal

sea level at the La Jolla tide gauge, precipitation, and reference evapotranspiration (Section 1.2.2). Hourly predictions of the La Jolla tide and non-tidal sea level were included as separate inputs in the Pastas model because it is known that groundwater response to periodic ocean variability is frequency-dependent (Ferris 1952; Jacob 1950). We used default water level settings and exponential response functions, each with a free scaling and decay parameter. We chose an exponential response function rather than the commonly used Gamma response function for several reasons: observed groundwater response to La Jolla tide gauge measurements at both time scales is almost immediate (<1 hour lag), and model fit for the exponential function was equivalent to and introduced fewer free parameters than the Gamma function. The hourly precipitation and ET_0 time series were combined within a linear recharge model component in Pastas and filtered through a single fitted Gamma response function. The Gamma response function is defined by a scaling parameter and two shape parameters, one that determines the rate of increase (in groundwater levels) from the ‘impulse’ and one that determines the decay rate of that response.

To select the desired combination of model input variables and associated parameterization of the model, we incrementally added inputs and evaluated model performance using model fit (R-squared) and error metrics: the root-mean-square error (RMSE), maximum model residual, and model skill (one minus the normalized mean square error or NMSE). We also compared TJRTLNET (point-located) precipitation to inputs derived from drainage basin scale 1-km gridded daily surface weather data from Daymet V4 (Thornton et al. 2020) for the Otay River Basin, Tijuana River Basin, and both basins combined. Because representing the highest water table elevations was our primary modeling objective, we specifically evaluated how well the models simulated observed daily maximum GWT elevation.

The final Pastas model calibrated to the well 1 S Seacoast groundwater data, hereafter referred to as the “well 1 groundwater model”, uses data from the full observed

time series with 3 years of model spin-up. In order to evaluate the sensitivity of the model to overfitting, we calibrated the model using 5 different time window partitions of the observation period data into calibration and evaluation periods. We calibrated the model using the following: the first 25% of data (8 December 2021 through 21 April 2022), the last 25% (1 January 2024 through 14 May 2024), the first 50% (8 December 2021 through 30 October 2022), the last 50% (1 November 2022 through 14 May 2024), the first four-month rainy period (1 January 2022 through 30 April 2022), and the last four-month rainy period (15 December 2023 through 15 April 2024), each with 3 years of model spin-up. For each calibration period, we evaluated the model on the remainder of the observed time series.

1.2.4 Generation of Hindcasts and Projections

We generated an hourly groundwater hindcast from 20 February 2003 through 30 September 2024 for well 1 (S Seacoast) by driving the calibrated groundwater model with data inputs from the hindcast period (Figure 1.2a). The hindcasts enable comparisons of recent and projected GWT and depth to water table. To estimate hindcast uncertainty we calculate a standard model error using the variance of the model residuals and combine it with the estimated GWT measurement error (Section 1.2.1), assuming uncorrelated normal probability density functions. Similarly, we generated groundwater projections from 1 October 2024 through 31 December 2099 at an hourly resolution for the five SLR scenarios (Figure 1.2b). We used the 50th percentile intermediate SLR scenarios because they are the best match to observation-based extrapolations of sea level at the La Jolla tide gauge out to 2050 (Sweet et al. 2022). For each projection year, we generated 200 groundwater realizations (25 NTR realizations combined with the 8 CMIP6-derived recharge inputs) from which we computed ensemble statistics. For each SLR scenario, we estimate projection ensemble uncertainties associated with unknown future non-tidal sea levels and recharge. The variances in recharge and the synthetic non-tidal residual

sea levels, not including mean sea level rise, do not significantly vary over the projection timeframe, so we compute a single mean ensemble uncertainty. We combine the mean ensemble uncertainty with the model uncertainty assuming they are uncorrelated. Finally, to incorporate uncertainties in the future SLR curves, we combine uncertainties using the 17th and 83rd percentile values from Sweet et al. (2022).

1.2.5 Development of Flood Metrics

For each of the 5 SLR scenarios, we computed metrics of groundwater emergence above the road elevation at S Seacoast every year through 2099 using the 200 hourly realizations of projected GWT. We derived the road elevation from a 2016 aerial LiDAR digital elevation model (Young et al. 2018). The emergence metrics include annual summaries of the distribution of ponding depths, emergence event durations, total number of days and duration of groundwater emergence, and emergence events by season and time of day. We selected these minimally redundant metrics based on similar literature regarding high tide flooding (e.g., Thompson et al. 2021), urban stream baseflow metrics (Hamel et al. 2015), and the needs of Imperial Beach city planners. We define summer as April through September and winter as October through March of the following year; daytime as 12am – 12pm UTC (4am – 4pm PST / 5am – 5pm PDT) and nighttime as 12pm – 12am UTC (4pm – 4am PST / 5pm – 5am PDT of the following day). These daytime and nighttime designations are chosen for practical implementation using the UTC time zone without daylight savings time. This example distinguishes between flooding happening mainly during daytime or nighttime hours, but other designations are possible depending on the application.

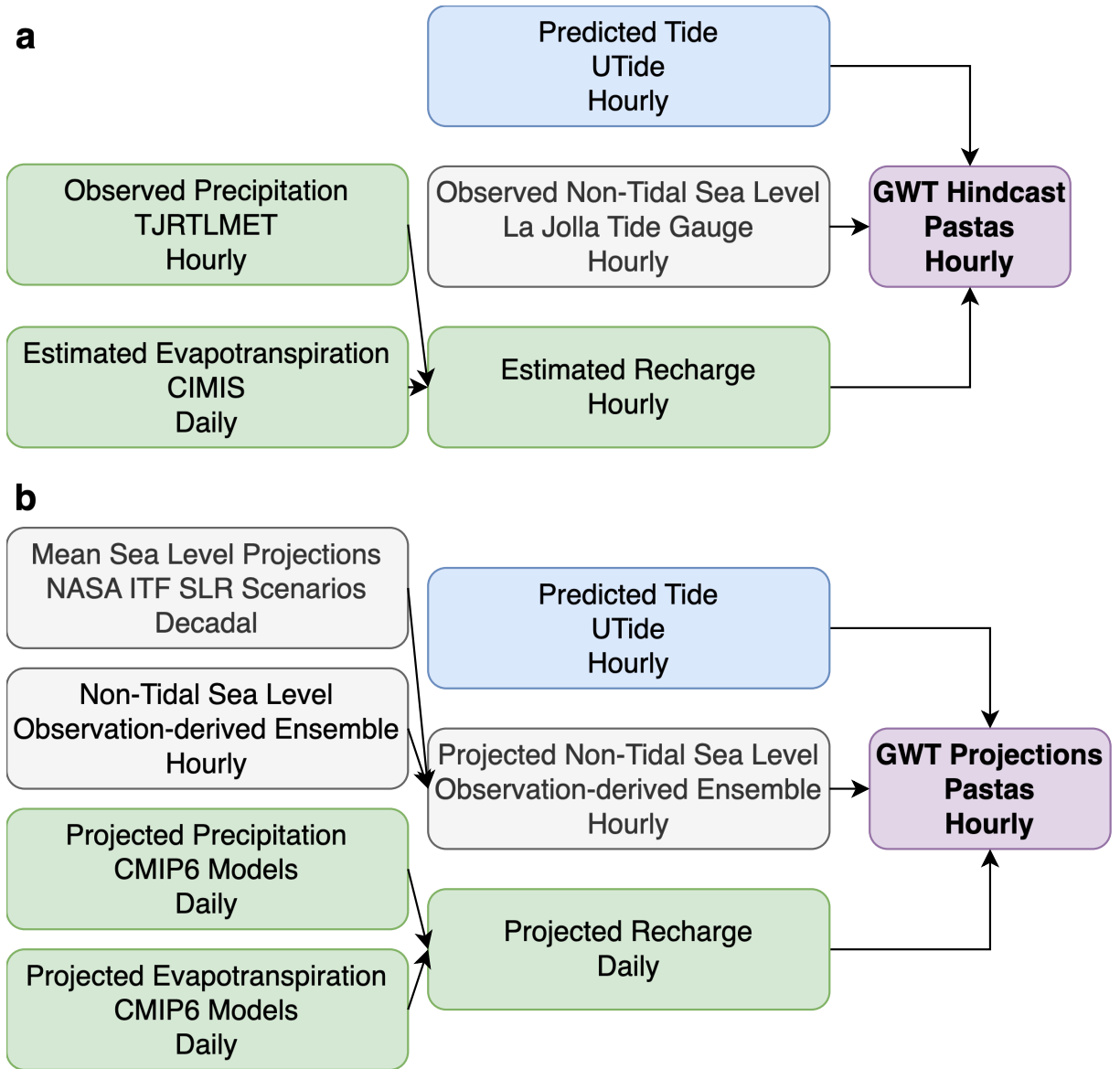


Figure 1.2. GWT model inputs, sources, and time resolutions for the (a) hindcast and (b) projection periods.

1.3 Results

1.3.1 Groundwater Observations

GWT time series collected 8 December 2021 through 14 May 2024 from the four wells reveal tidal efficiencies, TE , of 0.393 at the coastal well (1), 0.007 and 0.008 near the estuary (2) and San Diego Bay (3), respectively, and no discernible tidal influence at well 4 in the interior of the city (Figure 1.3a):

$$TE = \frac{\Delta h}{\Delta H} \quad (1.4)$$

where Δh is the hydraulic head change in a well corresponding to the tidal stage change ΔH . Preliminary versions of these results were previously reported in Sangsefidi et al. (2023b) with estimates of tidal lag. Observations are consistent with the USDA surface soil map showing two distinct geologies (Soil Survey Staff). Along the coastline, sandy dune deposits with relatively coarse grains and high permeability allow for efficient propagation of ocean tides through the aquifer as seen in well 1. Dense clays found at wells 2, 3, and 4, damp ocean signal propagation into the unconfined aquifer. Wells 2 and 3 are approximately 1 and 2 km from the coastline, respectively. However, they are both less than 100 m from tidal-linked bodies of water. It is not clear exactly what tidal amplitudes and phases are present in surface waters nearest wells 2 and 3, given that the estuary and bay geometries, respectively, may affect tidal attenuation.

The GWT at well 1 already approaches the road surface at S Seacoast at high tides. During our observations, depth to groundwater was consistently less than 50 cm and came within 7 cm on 8 February 2024 at 15:00 UTC during a 1.99 m high tide (Figure 1.3b). High tides at well 1 lag the La Jolla tide gauge by less than 30 minutes, preceding the estuary high tides in the Oneonta Slough (measured approximately 200 m northeast of well 1 in the main river arm of Figure 1.1a) by an additional 30 minutes (NERRS). The daily

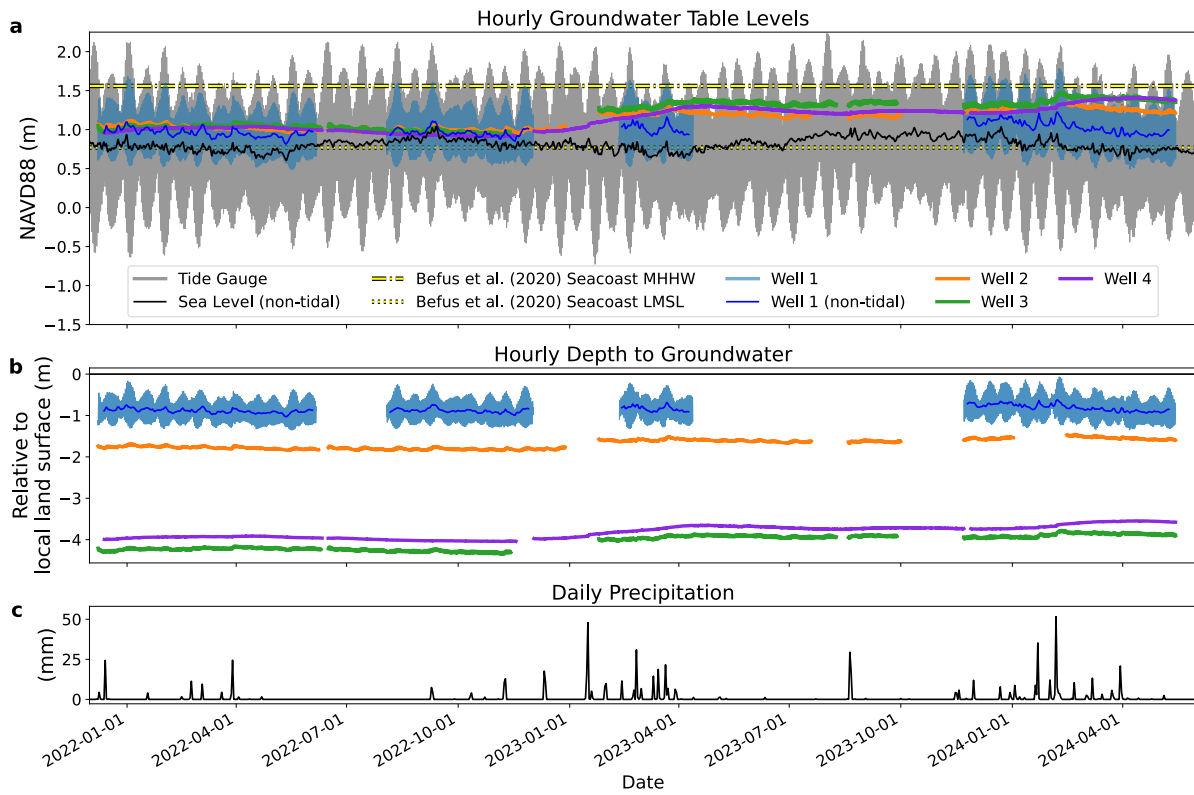


Figure 1.3. Observed GWT hourly time series relative to (a) NAVD88 and (b) local land surface; (c) observed precipitation from the TJRTL MET station.

non-tidal GWT at well 1 is correlated with the non-tidal sea level ($r=0.57$) and similar in amplitude with no discernible lag (Figure 1.3a). During a majority of the observation period, the well 1 non-tidal GWT is elevated around 20 cm above the non-tidal sea level. However, that gap decreases to less than 10 cm around October 2022, after 6 months of very little precipitation, and increases once precipitation begins in the winter of 2022-2023. This suggests that in addition to responding to the primary drivers of ocean tides and non-tidal ocean variability, recharge contributes an additional 10-20 cm of groundwater elevation. The Befus et al. (2020) model predicts that the groundwater surface elevation along the entirety of Seacoast Drive matches the ocean boundary condition (LMSL or MHHW) to within 2 cm using hydraulic conductivity values of $K = 0.1, 1$, and 10 m/day. The LMSL and MHHW end members bracket a majority of our observations at well 1, but the GWT does exceed the MHHW prediction, most often during spring tides combined with periods of significant precipitation (e.g., December 2023 to February 2024, Figure 1.3a).

In contrast to well 1, GWT at wells 2, 3, and 4, exhibit coherent behavior and appear more affected by recharge than by ocean variability. The ranges between the highest and lowest observed GWT at wells 2, 3, and 4, are all less than 60 cm (Table 1.1), and at any given time the GWT (relative to a common vertical datum) varies less than 20 cm among these three locations. The GWT surface and depth to groundwater in the dense clay appear to be primarily determined by recharge and local topography. The Befus et al. (2020) model for current sea level significantly overpredicts the tidal variability at wells 2, 3, and 4 for all values of K tested. For wells 2 and 3, the hydraulic conductivity that best matches the observed range of groundwater elevation is $K = 1$ m/day, consistent with Sangsefidi et al. (2023b). However, the Befus et al. (2020) model with $K = 1$ m/day predicts tidal ranges of 0.4 and 0.7 m between LMSL and MHHW at wells 2 and 3, respectively, while observations show that the ocean tides account for less than 0.1 m of range. At well 4, an unreasonably high value of $K = 10$ m/day offers the

Table 1.1. Comparison of GWT with Befus et al. (2020) Modeled Range

Well	Observed range (m,NAVD88)	K=0.1 m/day modeled range (LMSL-MHHW)	K=1 m/day modeled range (LMSL-MHHW)	K=10 m/day modeled range (LMSL-MHHW)
Well 1	0.5 - 1.8	0.8 - 1.6	0.8 - 1.6	0.8 - 1.6
Well 2	1.0 - 1.4	1.9 - 2.0	1.2 - 1.6	0.8 - 1.6
Well 3	0.9 - 1.5	1.2 - 1.8	0.9 - 1.6	0.8 - 1.6
Well 4	0.9 - 1.4	3.7 - 3.9	1.6 - 2.0	0.9 - 1.6

best match to observations but predicts 0.7 m of tidal variability where no tidal influence is observed. While a much smaller hydraulic conductivity seems more reasonable given observed tidal damping, these models increase the GWT at well 4 well above observed levels. Further analysis of these discrepancies is beyond the scope of this paper, but they highlight how important local geology is for determining both the mean GWT and its variability at different time scales. Because the GWT at wells 2, 3, and 4 do not vary significantly over the observation record and are far from emergent at those locations, we focus our modeling efforts on well 1.

1.3.2 Groundwater Model for S Seacoast

Model Performance

We modeled hourly GWT using inputs from the full study period with 3 years of model spin-up. When we modeled hourly GWT using the predicted La Jolla tide as the only input to the Pastas model, we achieved a model skill of 0.87 with an RMSE of 8 cm. Integrating non-tidal sea level variability increased model skill, decreased errors, and most importantly achieved a significant increase in the ability to predict the daily maximum GWT elevation (Table 1.2). Further integrating both precipitation and ET_0 within the model's representation of groundwater recharge resulted in the best model performance (model skill = 0.95, RMSE = 5 cm).

The well 1 groundwater model predicts observed groundwater variations to within 19 cm. Model residuals are greatest near the end of the observation record starting during

Table 1.2. Groundwater Model Performance

Model Components	RMSE (m)	Maximum model residual (m)	Model skill 1-NMSE	RMSE of daily max GWT (m)	R^2 of daily max GWT
Tide only	0.08	0.32	0.87	0.09	0.64
Tide+non-tidal ocean	0.07	0.30	0.91	0.07	0.76
Tide+non-tidal ocean +precipitation	0.06	0.21	0.93	0.06	0.83
Well 1 Groundwater Model: tide+non-tidal ocean+recharge	0.05	0.19	0.95	0.05	0.87

the winter of 2023-2024. While ocean tides contribute approximately 1 m of the amplitude variations, the non-tidal ocean variability and recharge each contribute approximately 30 cm (Figure 1.4). The model captures the seasonal cycles of elevated ocean water levels during summer and elevated recharge during winter.

Sensitivity Analyses

Separation of ocean water levels into tidal and non-tidal model inputs improves model agreement with observations. The TJRTLNET precipitation time series performed as well or better than basin-scale precipitation in terms of model skill, RMSE, and R-squared statistic. The linear recharge model resulted in significantly greater model agreement with observations than all other recharge model options. Inclusion of estimates of wave setup as an input did not improve model skill, though one of the largest wave events during our observation period (January 2024) corresponds to the greatest model underprediction of observed GWT elevation.

We evaluated the sensitivity of the Pastas model to overfitting using 5 different time window partitions of the observation period. Model skill, RMSE, and R-squared did not vary significantly among these 5 calibration time periods. Parameters of the recharge model component of the Pastas model were the most sensitive to the calibration time period, while parameters related to tidal and non-tidal ocean variability were relatively

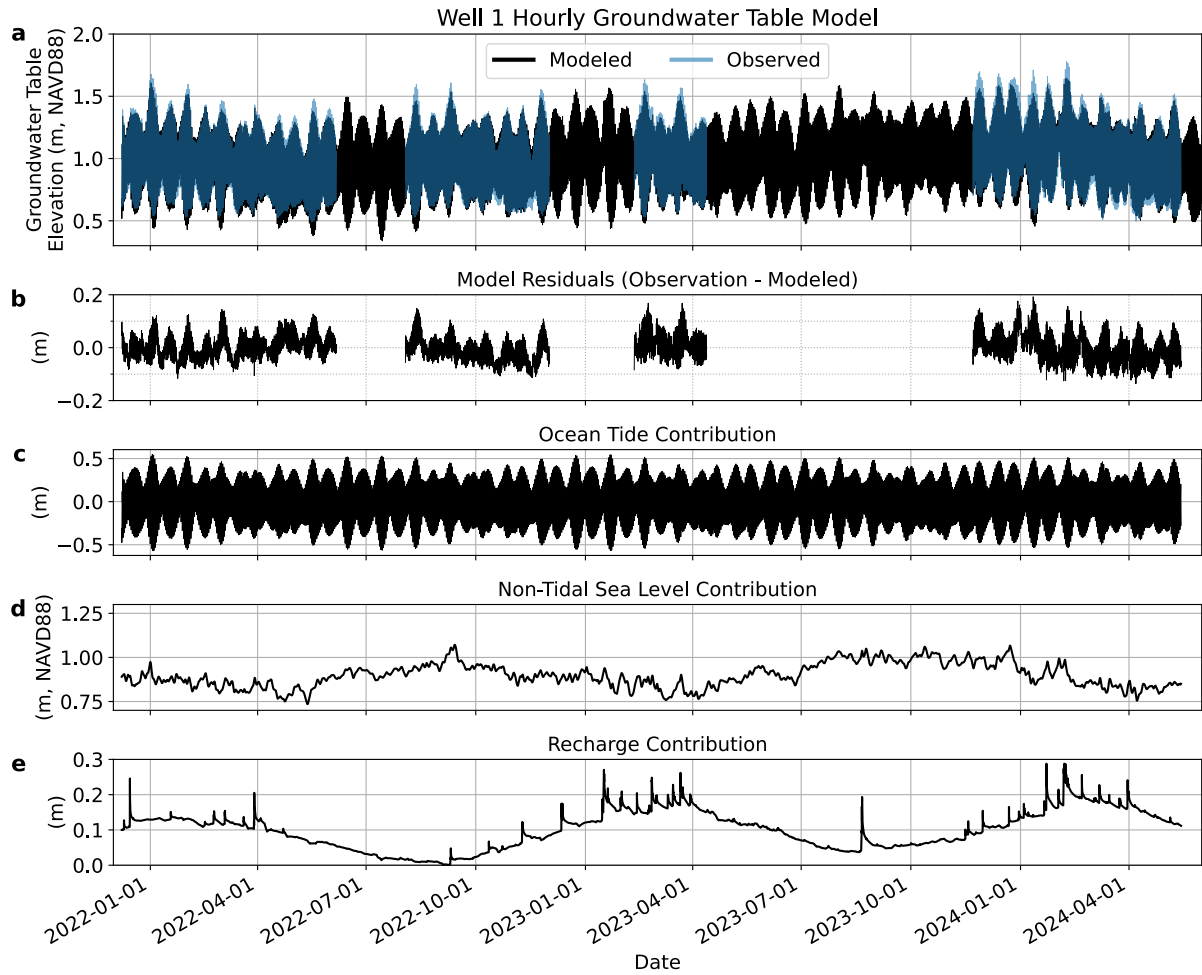


Figure 1.4. (a) Groundwater model comparison with observations, (b) model residuals, and individual contributions from the (c) ocean tide, (d) non-tidal sea level, and (e) recharge.

insensitive. Regardless of individual parameter sensitivity, we found model fit to be consistent regardless of the calibration period. Thus, we determined that model overfitting was not a significant issue for our application of the model, supporting our use of the full observed time series with 3 years of model spin-up to calibrate the well 1 groundwater model.

1.3.3 Groundwater Hindcasts and Projections for Seacoast Drive

According to the hindcast and projection of daily maximum GWT elevation (Figure 1.5), GWT emergence above the S Seacoast road elevation first occurs in 2065, and thereafter is increasingly emergent. The reported range of projections predict that emergence at this location could occur much earlier in the 2040s due to increased SLR, relatively high non-tidal sea level variability (e.g., El Niño), high levels of recharge, or combinations of these factors. Based on road elevation, S Seacoast will be the first low point of Seacoast Drive to flood. According to the five computed groundwater emergence metrics for S Seacoast (Figure 1.6), groundwater emergence above the S Seacoast road elevation does not necessarily result in an impactful flood. The amount, duration, frequency, and timing of ponding will determine whether emergence events result in disruptive flooding. A majority of GWT emergence events are shallow (<10 cm), short-lived (<5 hrs), and intermittent (<10 days per year) until 2070. All metrics begin to increase in the 2070s as extreme events are predicted to approach and potentially exceed the 25 cm safe limit for emergency vehicles (Green et al. 2017). Consistent with the timing of the highest tides of the year along this coastline (Ray and Merrifield 2019), our model predicts that the first groundwater emergence events will occur during the daytime in winter months, compounding flooding that already occurs from high wave over wash and heavy rainfall events. Starting in 2080 more events will follow during the summer nighttime hours. By the end of the century nearly every day will have emergent groundwater, and some events

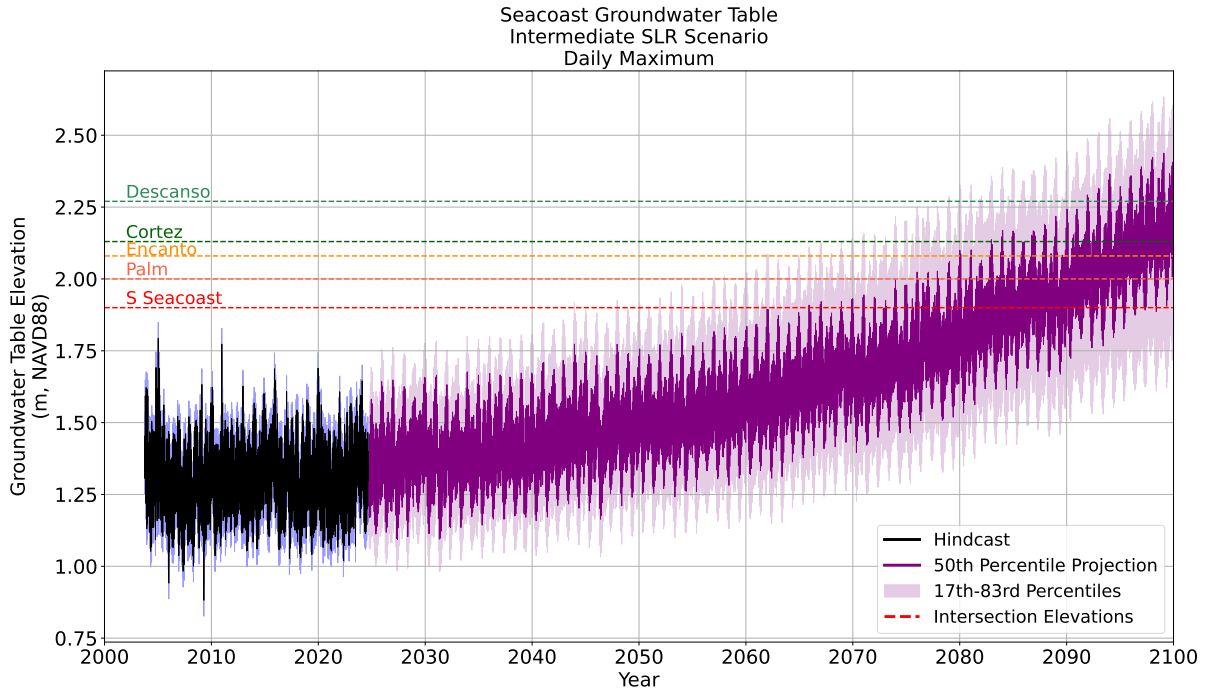


Figure 1.5. Seacoast GWT hindcast (2003-2024) and projection (2024-2100) daily maxima for the intermediate regional SLR scenario (Sweet et al. 2022).

will be extreme in both depth and duration. Figures S7-S11 show the full hourly GWT projections under 5 SLR scenarios. Figure S12 shows the hourly GWT projection for the year 2086 under the intermediate SLR scenario. Figures S13-S17 show the flood metrics at S Seacoast under 5 SLR scenarios, and figures S18-S21 show the flood metrics at 4 other low-lying intersections along Seacoast Drive under the intermediate SLR scenario.

We compute the annual mean of daily maximum simulated GWT elevations for each of the five SLR scenarios for intercomparison (Figure 1.7). Discontinuities between the hindcast and projections in 2024 are due to the projected sea level rise curves, which are relative to 2000 LMSL and start at a higher value in 2024 than the observed sea level, which in 2024 appears to be relatively low due to natural inter-annual variability (see Barnes_SupplementalS1.pdf figures S5 and S6). In the 50th percentile projections, the annual mean of daily maximum GWT elevation exceeds the road elevation at S Seacoast in 2062, 2068, and 2086 under the high, intermediate high, and intermediate SLR scenarios,

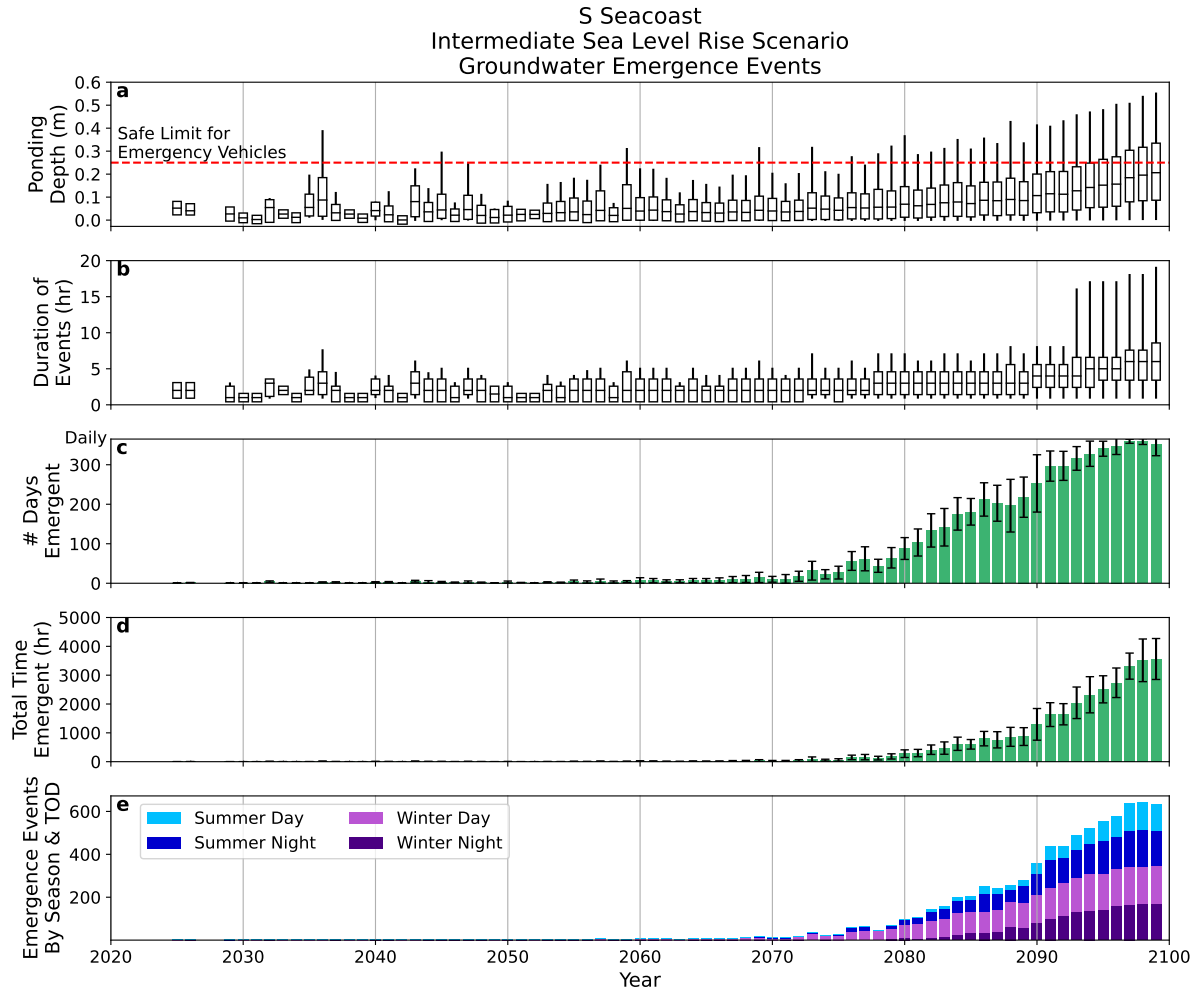


Figure 1.6. Annual S Seacoast groundwater table emergence metrics derived from the 50th percentile intermediate regional sea level rise scenario projections: full ensemble distributions of (a) maximum ponding depths and (b) ponding durations showing the 1st, 25th, 50th, 75th, and 99th percentiles; ensemble mean and standard deviation of (c) total number of days emergence occurs (vertical axis limited to the maximum of daily emergence) and (d) total time of emergence; (e) ensemble mean distribution of emergence events by season and time of day.

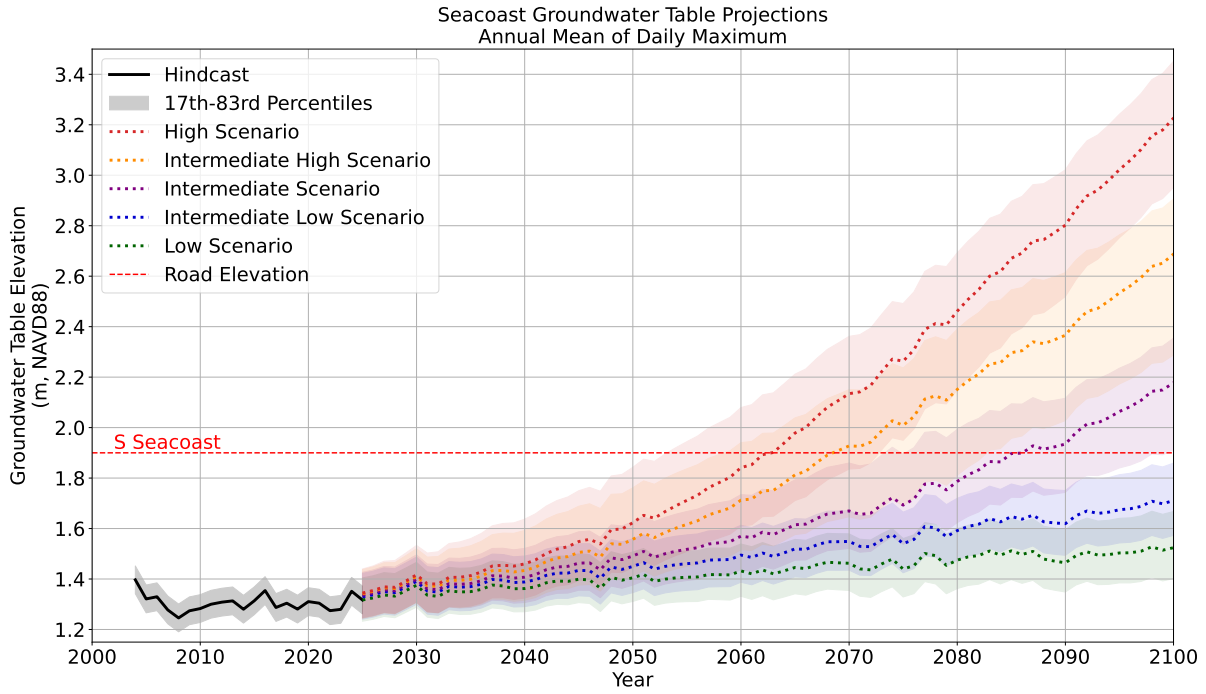


Figure 1.7. Seacoast groundwater table elevation hindcast (2003-2024) and projection ensemble annual averages of daily maxima (2024-2100) for the regional sea level rise scenarios (Sweet et al. 2022). Projected sea level rise curves are relative to 2000 local mean sea level and start at a higher value in 2024 than the observed sea level, which in 2024 appears to be relatively low due to natural inter-annual variability.

respectively, indicating frequent emergence. This threshold is not exceeded under the intermediate low and low SLR scenarios this century, but emergence still occurs at least several times per year by 2080 under these two scenarios.

1.4 Discussion and Conclusions

Our results show that the observed groundwater response at S Seacoast (well 1) is driven primarily by the ocean tides (Figure 1.4). The non-tidal sea level variability and seasonal recharge are both secondary and add equal but partially opposing contributions. Precipitation appears to elevate groundwater head over the mean ocean level before it slowly drains out over the course of dry summers (Figure 1.3). The other three observation locations near the Tijuana River Estuary, San Diego Bay, and at the city interior are

situated in dense clay that efficiently damps ocean tidal variability in the GWT. Close to the estuary (well 2) and bay (well 3), ocean tidal variability is less important than seasonal groundwater fluctuations caused by recharge. Ocean variability on sub-seasonal time scales does not likely play a significant role in groundwater emergence or flooding. In the interior of the city (well 4), there is no discernible sub-seasonal ocean influence and the GWT appears to be entirely dependent on recharge during the study period. These results are consistent with the USDA soil geology of the area for the upper unconfined aquifer on which the city is built. In this part of the city, our results suggest that depth to groundwater and the threat of emergence are determined by the topography of the city, recharge, and the mean sea level (Sangsefidi et al. 2023b). While tidal variability is of little importance for GWT in the dense clay, it severely impacts gravity drainage of stormwater infrastructure, with implications for urban flooding during coincident high tide and precipitation events.

Over 20% of the San Diego County coastline is within 200 m of the same highly transmissive soil geology of Seacoast Drive (see figure S22 in Barnes_SupplementalS1.pdf). Low-lying areas include Naval Base Coronado, parts of Camp Pendleton, and highly developed coastal towns from Carlsbad down to Del Mar. This study demonstrates that these parts of the coastline are vulnerable to the same groundwater emergence threats from SLR as Imperial Beach, and their risk should be further investigated. We recommend collecting GWT time series over several tidal cycles at several locations extending inland from the shoreline to model tidal attenuation as a function of distance from the coast (e.g., Housego et al. 2023).

Comparisons with the groundwater model of Befus et al. (2020) reveal that the LMSL and MHHW ocean boundary conditions capture a majority of our GWT observations near the coast (Figure 1.3). However, for any of the three specified hydraulic conductivities, the Befus et al. (2020) model does not simultaneously match both observed mean groundwater heads and tidal amplitudes at wells 2 - 4 (Table 1.1). Our observations at S Seacoast

exceed the MHHW mark frequently near the end of our record during combinations of spring tides and periods of precipitation. Static models like those of Befus et al. (2020) are a useful foundation from which to begin investigations of GWT behavior along the California coastline. They provide estimates of GWT, their responses to SLR, and aquifer properties, but direct observations of time-varying groundwater behavior are necessary to constrain models and understand complex aquifer behavior. Time series analysis not only tests the LMSL and MHHW boundary conditions, but enables exploration of the considerable ocean variability that can affect GWT at both low (non-tidal) and high (tidal) frequencies, and provides a way to examine the relative importance of recharge.

Our empirical Pastas groundwater model is 1-dimensional and therefore has limitations and assumptions that are important to note. This model implicitly assumes that regional groundwater flow that will discharge into the ocean and estuary is captured by the modeled response to recharge. The modeled response to recharge attempts to describe aquifer response to both local and regional precipitation and evapotranspiration. Further study is needed to assess the model's ability to capture both effects, especially if there is significant regional variability in these factors. Drainage of emergent groundwater is not considered; therefore, groundwater elevations above the road surface reflect the assumption that passive drainage into the ocean or estuary is not possible. This assumption is supported by the fact that ocean and estuary levels often equal or exceed the groundwater table elevation at well 1.

Our groundwater model hindcast and projection estimates show that co-occurrence of extreme sea levels and precipitation events increases the probability of groundwater emergence. Our projections under the intermediate SLR scenario predict groundwater emergence at the lowest parts of Seacoast Drive (S Seacoast) beginning around 2065 and show frequency and magnitudes of emergence increasing rapidly towards the end of the century (Figures 1.5 and 1.6). Buried infrastructure and road integrity will be compromised well in advance of consistent groundwater emergence (Knott et al. 2017).

For city planners concerned with flood mitigation and response, it will be important to track which SLR trajectories the regional sea levels follow in coming decades in order to update GWT projections (e.g., Figure 1.7), especially given the uncertainties in our understanding and modeling of ice-sheet melting and its contribution to SLR (e.g., Bradley and Hewitt 2024). This study relies on assumptions that the relationships between drivers of groundwater variability will not change significantly this century and can be modeled using data from a two-year observational window. Given the proximity of well 1 to the ocean boundary condition and consistency of mean GWT projections made here with the static, physics-based MODFLOW model developed by Sangsefidi et al. (2023b), we believe our extrapolations are reasonable. We incorporate uncertainties in data, groundwater model parameters, SLR scenarios, and global climate models to suggest a range of likely GWT elevations.

Local climate change adaptation planning efforts (e.g., City of Imperial Beach 2024) consider flooding along Seacoast Drive from the ocean in terms of wave overtopping and beach erosion, and overflow from the estuary into the street, but not the pernicious threat of groundwater emergence. Our study shows that under intermediate and higher SLR scenarios, GWT emergence will become a considerable flooding issue by mid- to late-century and must be considered in the same planning horizons. Proposed mitigation efforts protecting against ocean and estuary flooding would be rendered ineffectual if groundwater emergence is not addressed, and may even exacerbate groundwater flooding (de Schipper et al. 2021; Ludka et al. 2018). Here, we model groundwater level variation as a parsimonious function of climate and SLR at a representative coastal location, using open-source data and modeling tools. This study advances our understanding of compound threats from SLR to coastal communities and demonstrates a straightforward modeling approach that may be used immediately and in the future for understanding adaptation needs and timelines in Imperial Beach and in other coastal communities.

ACKNOWLEDGEMENTS

Support for this study was provided by the U.S. National Science Foundation (2113984, 2113987, 2239602, and 2205239), by the U.S. Army Corps of Engineers (W912HZ1920020), and by the California Department of Parks and Recreation, Natural Resources Division Oceanography Program (C19E0026). We would like to thank Chris Helmer, Meagan Openshaw, Brian Leslie, Mark Benrubi, and others from the City of Imperial Beach for providing guidance, resources, permits, and access for this research. Brian Woodward and Kent Smith from UCSD Scripps Institution of Oceanography (SIO) provided guidance, materials, and sensors for the project. Pacific Drilling installed and destroyed the groundwater monitoring wells. Wesley Danskin from the US Geological Survey, Britt Raubenheimer from the Woods Hole Oceanographic Institute, Rachel Housego from Penn State, Sarah Giddings from UCSD SIO, and Jeff Crooks from the Southwest Wetlands Interpretive Association provided additional research guidance.

Chapter 1, in full, has been submitted for publication of the material as it may appear in *Earth's Future*. Barnes, Austin T.; Merrifield, Mark A.; Bagheri, Kian; Levy, Morgan C.; Davani, Hassan, American Geophysical Union. The dissertation author was the primary investigator and author of this paper. The supplemental information was also submitted as part of this publication.

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Chapter 2

Rising Sea Levels and the Increase of Shoreline Wave Energy at American Samoa

2.1 Introduction

American Samoa, currently an unincorporated United States territory in the South Pacific, is comprised of 5 main islands and 2 coral atolls, with Tutuila being the largest (142.3 km²), most populous (>60,000) island (Figure 2.1). Located near a semidiurnal tidal amphidrome, Tutuila experiences a small tidal range with 0.394 m mean high water (MHW) and 0.435 m mean higher high water (MHHW) above mean sea level (MSL) (NOAA CO-OPS). Similarly, semiannual (i.e., King Tides) and 4.4-year modulations of extreme high tides are weak (Ray and Merrifield 2019). Due to the low tidal variability and Tutuila's steep topography and narrow coastal plain, a majority of the population and infrastructure is located adjacent to the coastline, and is therefore highly vulnerable to storms, wave-driven flooding events, and sea level rise (SLR) (Dobson et al. 2021).

In September of 2009, a magnitude 8.1 Samoa-Tonga earthquake doublet caused a devastating tsunami and subsequent land subsidence. In 2013, the American Samoa Sea Grant extension agent noticed a distinct increase in sea level in National Oceanic and Atmospheric Administration's (NOAA) Pago Pago tide gauge (1770000) record following

the 2009 earthquakes (NOAA Tides & Currents). Accelerated subsidence was confirmed for both Samoa and American Samoa (Widlansky et al. 2017), and was subsequently federally recognized in 2019 following studies linking the subsidence to the 2009 earthquake doublet (Han et al. 2019; Caccamise 2019). Based on NOAA’s Pago Pago tide gauge, satellite altimetry, and Global Navigation Satellite System land motion data, it was found that prior to the 2009 Samoa-Tonga earthquake doublet, land subsidence of Tutuila was occurring at an average rate of 1-2 mm/year. After the earthquakes, average rates of land subsidence increased to 16 mm/year during the period of 2009-2017 (Han et al. 2019). While the rate of land subsidence has been slowing since 2009, it is expected to continue at well above pre-2009 rates for several decades due to viscoelastic relaxation, resulting in 30-40 cm of relative SLR this century, independent of global SLR (Han et al. 2019), equivalent to total SLR 4-5 times greater than the global average (Huang et al. 2022). Updated relative SLR projections integrating future SLR for various socio-economic pathways provided by the United States Interagency Task Force (ITF) with land subsidence estimates were recently released for an American Samoa Sea Level Rise Viewer (Baizeau et al. 2023). ITF estimates of SLR for American Samoa based on the intermediate emissions scenario would account for only 50% of total SLR by 2030, and by 2100 would underestimate total SLR by more than 0.2 m (Baizeau et al. 2023).

The main shoreline defense at Tutuila against energetic incident waves is a broad (up to 600 m), shallow (<2 m) fringing reef that encompasses much of the island (Figure 2.1). In general, coral reefs are highly efficient at dissipating incident sea-swell (SS) wave energy; e.g., Ferrario et al. (2014) estimate that reefs dissipate 97% of the incident energy ranging from typical to hurricane wave conditions. Field studies at islands with fringing reefs similar to Tutuila illustrate how waves break over the outer reef, with additional frictional dissipation over reef substrate at rates much higher than over sandy beaches (Lowe et al. 2005). In general, healthier reefs with greater reef canopy complexity have larger observed frictional dissipation rates (Monismith et al. 2015).

Energetic SS wave events carry the potential for severe impacts at island shorelines. Hoeke et al. (2013) describe a series of extreme coastal flooding events driven by swell from extratropical cyclones that impacted western Pacific islands in December 2008. In July 2022, the combination of King Tides and an energetic swell led to the worst coastal flooding since the 2009 Samoa-Tonga tsunami and was declared a major disaster by the U.S. Federal Emergency Management Agency (FEMA 2023). Storlazzi et al. (2004) observed that greater water levels over a fringing coral reef off of Moloka‘i, Hawai‘i, allowed more of the deep-water SS energy to propagate over the reef flat, increasing the potential for shoreline erosion (Storlazzi et al. 2011). Becker et al. (2014) considered observations from three fringing reefs in the Pacific and found that water level over the reef flats controls the amount of shoreline SS wave energy. The dependence of SS shoreline wave heights on water level varies from site to site in part because the amount of dissipation depends on reef width and bottom roughness in addition to water depth over the reef flat.

While fringing reefs are effective at damping SS waves, longer period infragravity waves (25 to 200 s) (Becker et al. 2016), far infragravity waves (200 to 1000 s) (Péquignot et al. 2009), and wave setup (Becker et al. 2014) can be energetic components of wave-driven shoreline water levels. Observations at Ipan reef, Guam, demonstrated that higher water levels increased the normal mode frequency of the fringing reef flat, and allowed for modal excitation of water levels in the far infragravity frequency band by wave-group forcing. The reef-flat modes have anti-nodes at the shoreline, resulting in increased low-frequency shoreline water level variation and therefore potential for flooding due to elevated water levels (Péquignot et al. 2009). When the combination of reef geometry and water level does not lead to the excitation of reef modes, however, coral reefs have been demonstrated to reduce low-frequency motion on the reef flat and wave runup at the shoreline (Buckley et al. 2018).

Reef-fringed island shorelines differ from continental sandy beach shorelines in that runup amplitudes on sloping sand beaches increase with steepening beach slope, but not

necessarily with water level. For example, the well-established statistical runup model of Stockdon et al. (2006) does not include a water level dependence, although beach slope may change with water level on non-uniform beach profiles. Climate change related projections of wave runup and coastal flooding on sandy beach shorelines thus depend on expected changes in the incident wave climate, e.g., due to changing storm patterns, or changes in shoreline morphology. The ability of island reefs to suppress wave energy is water-level dependent, and hence the influence of SLR may be twofold, causing both higher still water levels as well as higher wave energy. The inability of live reefs to accrete and keep pace with SLR is an additional potential concern. Absent other external stressors, relative SLR alone may potentially encourage reef growth, since reef accretion rates on shallow reef flats often are constrained by low tide and the lack of accommodation space (Kennedy and Woodroffe 2002). Conversely, continued ocean warming and acidification will likely lead to coral bleaching and mortality, inhibiting reef accretion (Dove et al. 2020). For the purposes of this study, we assume the reef bathymetry is fixed, and that relative SLR will increase the water depth over the fringing reef. Our projections are more closely tied to the water level over the fringing reef than to time, leaving room for the uncertainty in reef accretion and emissions pathway-dependent SLR.

Here we investigate how rising sea level over a fringing reef may affect nearshore swell wave heights, lower frequency wave heights and breaking-wave setup, and highlight possible impacts of total water level changes on American Samoa. A goal of this work is to support calls for immediate mitigation and adaptation planning and lay the groundwork for forecasting future flooding events that result from the combination of elevated water level and swell waves. We use a one-dimensional, phase-resolving non-hydrostatic wave model to emulate wave transformation over a fringing reef study site for a range of present and future sea levels. The work extends a similar coastal flooding analysis conducted on reef-fringed shorelines in the Marshall Islands (Merrifield et al. 2014); however, in this study the influence of increasing sea level on runup, and specifically SS wave energy, is

explicitly modeled. As in Merrifield et al. (2014), we hindcast total water level to assess the influence of recent relative sea-level rise at American Samoa on total water levels. We examine the effects of land subsidence associated with the September 2009 Samoa-Tonga earthquake doublet. We focus on total water levels that are likely to reach the elevation of the existing coastal roadway that is the main transportation artery for Tutuila.

2.2 Methods

2.2.1 Field Survey

Our study site is the fringing reef at Faga'itua Bay, a southern-facing shoreline in eastern Tutuila and home to five villages (Figure 2.1a). The Faga'itua Bay morphology is representative of other embayed fringing reefs around the island. The reef varies in width from approximately 260 to 600 m, and in fore reef slope for an average slope of approximately 1/6 at our site. Spur and grooves on the fore reef extend up to the reef crest, which is still exposed at the lowest tides. The reef flat is shallow (<2 m) and mainly reef rock. The shoreline around the bay is comprised of narrow (0-10 m) sandy beaches backed by rocky, vegetated slopes up to the main coastal road, which has a nominal elevation varying from 1.5 - 5 m (3.4 m at our transect location) above MSL. Wave breaking is typically confined to a narrow breaking zone at the outer edge of the reef flat.

From April to October 2017, three bottom-mounted pressure sensors (Sea-Bird SBE26plus) were deployed across the reef at Faga'itua Bay. The sensors were located offshore of the steeply sloping shoreline in deployment-averaged water depths of 0.57 m near the shore (A), 1.00 m at mid reef (B), and 8.55 m on the steep fore reef (C) (Figure 2.1b). Depths are referenced to MSL based on comparison with the National Oceanic and Atmospheric Administration (NOAA) Pago Pago tide gauge on Tutuila during the sampling period. To maximize battery life, measurements were collected at 1 Hz for 1.5 hour bursts every 3 hours. Intermediate water depth wave data from 2014 to present day

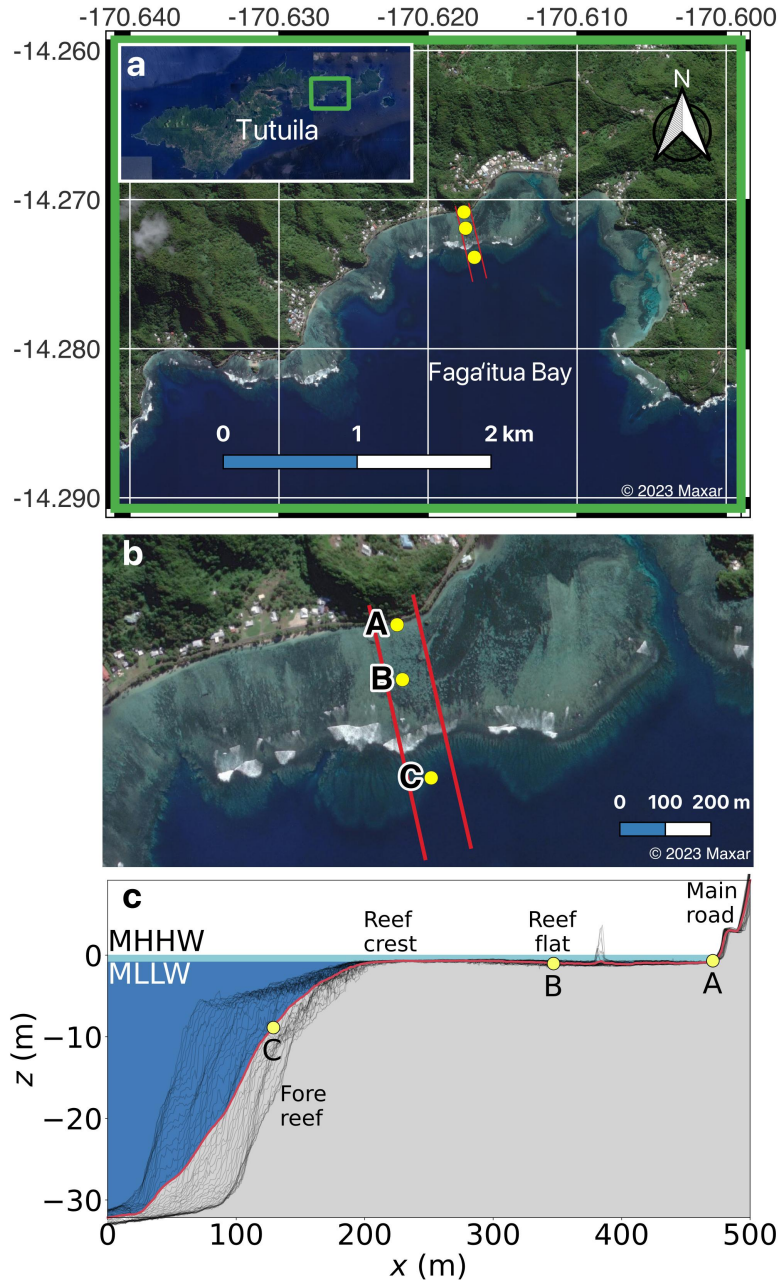


Figure 2.1. Faga'itua Bay, Tutuila, American Samoa and cross-shore transect. (a) Satellite imagery of Tutuila Island (inset) and Faga'itua Bay from Maxar. (b) A closer view of the reef and its variable coral cover. Pressure sensors deployed in 2017 are marked in yellow (A = nearshore, B = mid-reef, C = reef face) and the red lines mark the 100 m-wide section of reef from which we derive an average reef transect. (c) Average reef bathymetry 1D transect (red) derived from transects spaced every 2 m in the alongshore direction (black). Mean higher high water (MHHW) and mean lower low water (MLLW) are indicated (tidal datum analysis period 01-Oct-2011 to 30-Sep-2019), as well as the sensor locations, fore reef, reef crest, reef flat, and the main coastal road.

is available from the Coastal Data Information Program’s (CDIP) buoy station 189 at Aunu‘u. At our study site, the sandy beach has been recently lost to rising relative sea level.

We convert pressure time series to surface elevation using first-order linear wave theory, from which we calculate wave spectra and bulk wave statistics. The 1.5-hour bursts are broken into 30-minute records and detided by removing the dominant M2 tidal component. Atmospheric pressure measurements collected every 6 minutes from NOAA’s National Data Buoy Center (NDBC) station NSTP6 - 1770000 at Pago Pago are interpolated to match sensor samples and removed from total pressure measurements. For this study, we define the low frequency (LF) band, encompassing infragravity and far infragravity waves bands, from 0.001 - 0.04 Hz (periods of 25 - 1000 s) and the sea-swell (SS) band from 0.04 to 0.3 Hz (3.33 - 25 s). Records with water depth < 0.3 m are excluded from analysis. At Faga‘itua Bay, we have 2100 30-minute records during which both the nearshore (A) and reef face (C) sensors were operational. The reef flat (B) sensor had issues with timing and stability during deployment, so we use the observations for verification of the bathymetric depth only.

We compute the nearshore breaking-wave setup following Becker et al. (2014) from the 30-minute average water depths, h_A and h_C . Root-mean-square wave heights at sensor A, H_{rms}^A , and sensor C, H_{rms}^C , are computed over each 30-minute record as $2\sqrt{2}\sigma$, where σ is the standard deviation from the surface elevation spectrum in the SS frequency band. We exclude setup calculations for weak wave conditions ($H_{rms}^C - 1.2H_{rms}^A < 0.4$ m) when wave breaking is not expected to occur. For modeled setup, we use the default SWASH setup computation relative to the still water level (SWL) as defined by the initial water surface.

We compute the peak period by finding the peak frequency of the 1-dimensional wave spectrum, and the mean period following the National Data Buoy Center (NDBC) as

$$T_{mean} = (\frac{m_0}{m_2})^{1/2} \quad (2.1)$$

$$m_0 = \Sigma S(f)d(f) \quad (2.2)$$

$$m_2 = \Sigma S(f)f^2d(f) \quad (2.3)$$

where m_0 and m_2 are the zeroth- and second-order moments of the nondirectional wave spectra computed by summing the spectral density, $S(f)$, or $S(f) * f^2$ over all spectral frequencies, f , respectively. The NDBC refers to this as the zero-crossing period in some references. With only pressure sensors we did not measure wave direction; however, based on visual observations we assume shore-normal incidence of waves and insignificant reflection of wave energy.

2.2.2 Bathymetry

We specify a 1-m resolution cross-shore bathymetry transect at Faga'itua using a preliminary digital elevation model (DEM) provided by NOAA. We verify that the reef bathymetry at Faga'itua appears to closely match aerial photographs of alongshore variations including reef channels and smaller spur and groove features on the fore reef. Additionally, the relative depths of the 3 reef sensors match estimates of the mean water depths from observations to within 0.3 m. For the numerical modeling described in subsequent sections, we use a 500-m long, 1-dimensional grid from 32-m water depth to 10 m above MSL. We vary the cross-shore grid spacing from 2 m at the seaward boundary to 0.04 m at the shoreward boundary using linear interpolation. The input bathymetry has 3 grid points in the alongshore direction with 1-m spacing, and each cross-shore transect is identical. This single transect is derived from an average of parallel cross-shore transects spanning 100 m in the alongshore, spaced every 2 m (Figure 2.1c). Several transects include a rock protrusion but its impact on the final average transect are negligible. We

adjust the simulated still water level for each model run to match the reef face (sensor C) location water depth with the 30-minute average water level for that observation period.

2.2.3 1-D Numerial Modeling of Nearshore Waves using SWASH

Wave transformation across the Faga'itua reef is simulated by the phase-resolving non-hydrostatic wave model Simulating WAVes till SHore (SWASH) version 10.01. SWASH has been used to investigate waves over reefs with validation using laboratory experiments (Buckley et al. 2014, 2022; Franklin and Torres-Freyermuth 2022) and field observations (Risandi et al. 2020; Rijnsdorp et al. 2021; Lowe et al. 2015; Torres-Freyermuth et al. 2012). SWASH is a nonhydrostatic wave-flow model using the Reynolds-averaged Navier-Stokes equations (Zijlema et al. 2011). We implement SWASH on a 1-dimensional transect but use the 2-dimensional, nonhydrostatic mode of SWASH to employ variable cross-shore grid spacing described above, following Fiedler et al. (2018). We use 10 vertical layers and the default breaking wave parameter (Buckley et al. 2014). Turbulent mixing was activated using the vertical $k - \epsilon$ model (Launder and Spalding 1974) with default parameters. A background viscosity of $1 * 10^{-4}$ is assumed. Following Risandi et al. (2020), who studied a fringing reef in southwestern Australia with visually similar coral cover, we account for friction between the flow and rough bed using a constant friction factor of 0.05. SWASH is run with 15 minutes of spin-up time to allow breaking-wave setup to stabilize followed by 30 minutes of model time. We analyze the simulated sea surface elevation to compute wave spectra and significant wave heights in both the LF and SS frequency bands following the same methods used for the observations. The default SWASH method is used for computing wave setup.

At the offshore boundary we initiate simulations with 30-minute average wave spectra computed from the reef face (C) sensor observations, back-refracted from observation depth (~ 8 m) to the model boundary depth (32 m) using linear wave theory. We

neglect SS wave energy associated with reflections at the fore reef based on the findings of Péquignet et al. (2011) for a similar steeply sloping reef face. Time series of SS waves at the boundary are obtained from the back-refracted wave spectra assuming random wave phase. Of the 2100 observational records, a sample of 200 was chosen for numerical simulation and comparison. Of the 200 records chosen for the sample, 49 are the largest observed nearshore (A) water level records with $h_A > 0.9$ m to ensure that we compare model behavior at the highest observed water levels. The remaining 151 are randomly chosen to span the range of observed water levels and incident wave energy. Each of the 200 30-minute incident wave spectra are simulated using SWASH with observed water levels for model validation.

The validated model is extended to higher water levels by maintaining the wave and tide conditions used in the historical hindcasts and increasing the still water level (SWL) (e.g., due to tides, non-tidal residual sea level, SLR, and vertical land motion) to 0.6 - 2.0 m above current MSL. The range of SLR is chosen to extend observed water levels to end of century projections for American Samoa made by Baizeau et al. (2023), based on a combination of sea level rise resulting from the ITF intermediate emissions scenario and vertical land motion estimates Han et al. (2019). Baizeau et al. (2023) project 0.8249 m of relative SLR by 2070 and 1.4112 m by 2100, relative to 2005 MSL. We track the modeled runup line with a threshold depth of at least 0.01 m.

2.2.4 Nearshore Setup and Sea-Swell Wave Hindcasts

We perform a wave hindcast (January 1979 through May 2023) at Faga'itua Bay using observed water levels at the Pago Pago tide gauge, a deep water wave hindcast, and a refraction model over local bathymetry to estimate reef face (sensor C) significant wave height. Empirical relationships then are used to estimate breaking-wave setup and nearshore SS wave height (sensor A).

We obtain a wave hindcast dating back to 1979 for the reef face location (sensor C)

using an open-source WWIII-generated wave hindcast (Smith et al. 2020) and a linear spectral refraction model (O’Reilly et al. 2016). The WWIII hindcast provides hourly directional spectra around American Samoa. We obtain spectra from the output model grid point located at -14.53°N, 189.53°E, just to the south of the CDIP Aunu’u buoy, against which we validate the wave hindcast for periods of overlap. We use a non-stationary, linear spectral refraction wave model (O’Reilly et al. 2016) to generate a transfer matrix that is both a function of frequency and wave direction. The matrix is constrained with a cutoff of 130 degrees based on the geometry of Faga’itua Bay to prevent errant excess energy making it to our reef face location. We bias-correct the model using our observations from the 2017 field deployment. The refracted hindcast overpredicts some of the local high-frequency seas observed, and misses some other observed events, but overall has reasonable skill in matching observations ($R^2=0.63$, RMSE=0.18 m) from the 2017 field deployment.

We use observations from the 2017 field deployment to parameterize the nearshore breaking-wave setup as a function of the tide and the reef face significant wave height. As the observed setup at sensor A exhibits both a tidal and reef face wave height dependence, we follow Becker et al. (2014) to estimate a tidally dependent (h' , MSL) factor,

$$p(h') = 0.10h'^2 - 0.12h' + 0.26 \quad (2.4)$$

that, when multiplied by the reef face SS significant wave height, H_{SS}^C , provides an estimate of breaking-wave setup as

$$\bar{\eta}_A = p(\hat{h}')H_{SS}^C \quad (2.5)$$

A quadratic fit results in improved predictive skill ($R^2=0.87$, RMSE=0.02 m) compared to a linear fit ($R^2=0.45$, RMSE=0.02 m). This relationship is not meant to be extrapolated into higher sea levels beyond those observed (~ 0.7 m, MSL), but is useful for obtaining hindcast estimates of breaking-wave setup given observed water levels and

hindcast wave heights.

To estimate historical nearshore breaking-wave setup using the regression fit (eq 2.5), we use estimates of the reef face SS significant wave height, H_{SS}^C , computed using the wave hindcast. We then combine the observed sea level record from the Pago Pago tide gauge with our estimates of setup to obtain a total nearshore mean water level. We use model results discussed in the next section to estimate the nearshore SS significant wave heights from January 1979 through May 2023.

2.3 Results

The wave field at Faga'itua reef exhibits strong SS energy dissipation and LF energy propagation across the reef flat (Figure 2.2). Reef face (sensor C) SS significant wave heights (H_{SS}) range between 0.3 and 1.8 m, while nearshore (sensor A) H_{SS} never exceed 0.3 m (Figure 2.2b). Nearshore LF significant wave heights often equal or exceed the SS counterpart, and nearshore LF energy exceeds the LF energy observed at the reef face (Figure 2.2c,d).

The nearshore H_{SS} scales with the mean water depth over the reef flat (Figure 2.3), similar to the reefs studied for example in Becker et al. (2014). Nearshore H_{SS} are depth limited for the considered range of offshore wave conditions at Faga'itua. The depth limitation is set as waves break at the outer reef, i.e., waves break when their heights exceed a certain fraction of the water depth. Additional dissipation occurs as waves travel shoreward of the break zone due to bottom friction over the rough reef substrate and turbulent energy loss in the broken wave rollers, which both depend to some extent on water depth. The water level variations on the reef in turn are set by the tide, non-tidal residual sea level effects, and wave setup. For a given reef flat water level, the nearshore H_{SS} exhibits a dependence on the offshore wave height; however, this effect is weak compared to the water-level dependence. As in Merrifield et al. (2014), observed nearshore

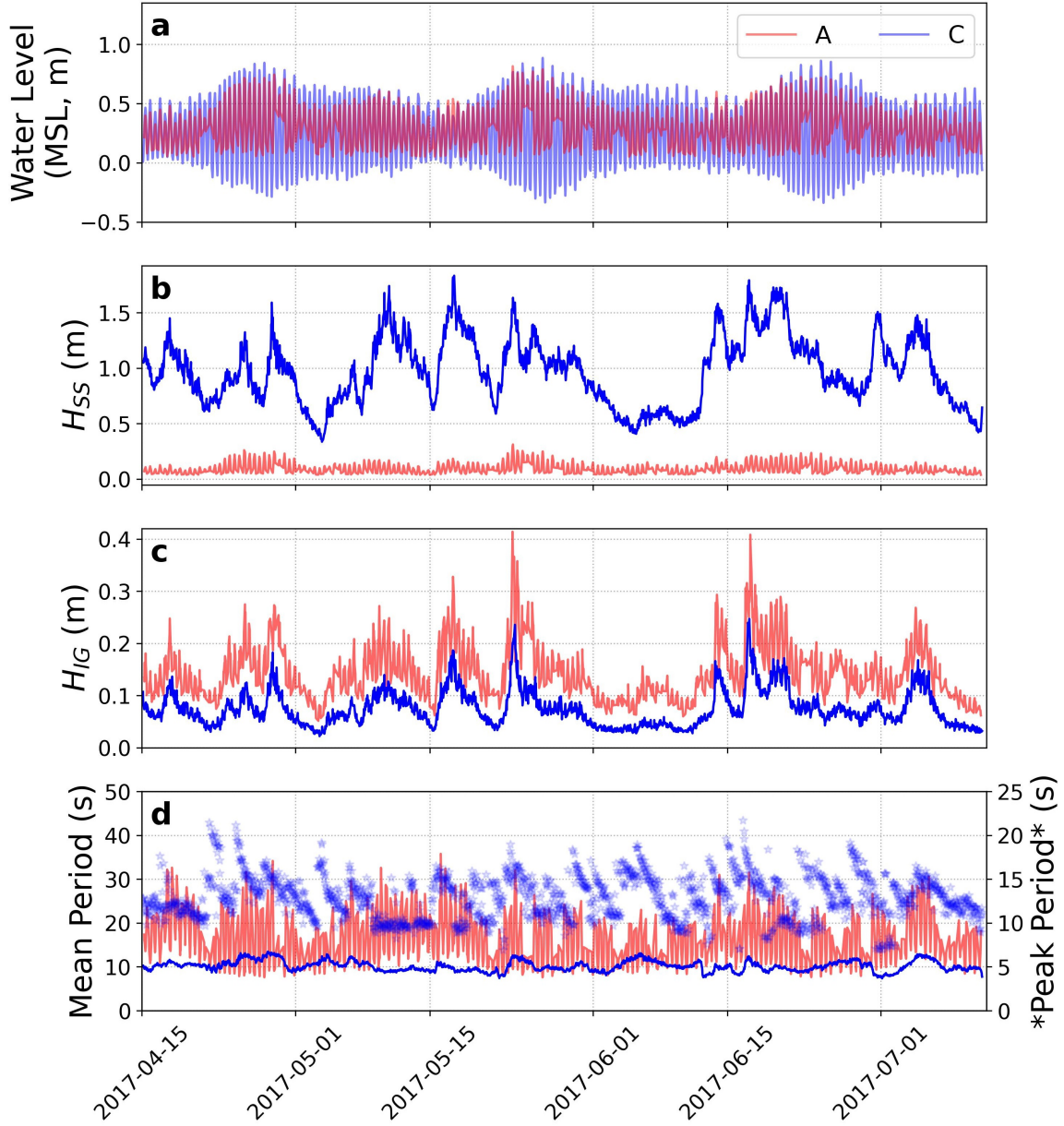


Figure 2.2. Observations from 2017 field deployment. Time series from sensor A (nearshore) and C (reef face) of: (a) 30-min average water level (MSL); (b) SS (0.04 - 0.3 Hz) significant wave height; (c) LF (0.001 - 0.04 Hz) significant wave height; (d) mean period (and peak period for sensor C only, shown in symbols).

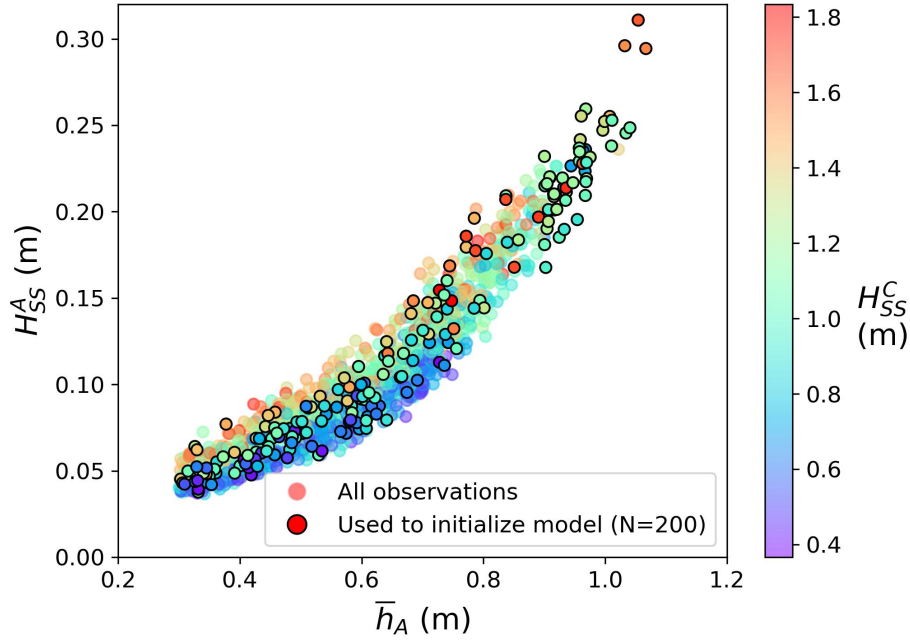


Figure 2.3. Nearshore (sensor A) sea-swell significant wave height as a function of mean water depth, colored by the observed significant wave height on the reef face (sensor C). All 30-minute average observations with water depth >0.3 m are shown; the 200 chosen for SWASH validation are marked with black borders. Nearshore sea-swell significant wave height is strongly depth-dependent, with weaker dependence on the reef face significant wave height.

H_{SS} may be estimated using a quadratic fit to mean water level, but to what extent may this be extrapolated to higher, unobserved water levels?

To explore how this water level dependence of H_{SS} will evolve with increases in water depth over the reef, we use a one-dimensional, phase-resolving nonhydrostatic numerical model, SWASH. Model simulations exhibit high skill (Figure 2.4) in matching observed nearshore H_{SS} with relatively low root-mean-square errors ($R^2=0.93$, RMSE=0.02 m). SWASH simulations also do reasonably well in matching the observed nearshore LF significant wave height (H_{LF} , $R^2=0.81$, RMSE=0.03 m) and breaking-wave setup ($\bar{\eta}_A$, $R^2=0.78$, RMSE=0.03 m). We hypothesize that model results deviate from observations due to 2-dimensional effects not captured in our 1-dimensional simulations.

Combining simulations for both observed and added sea levels, the model results

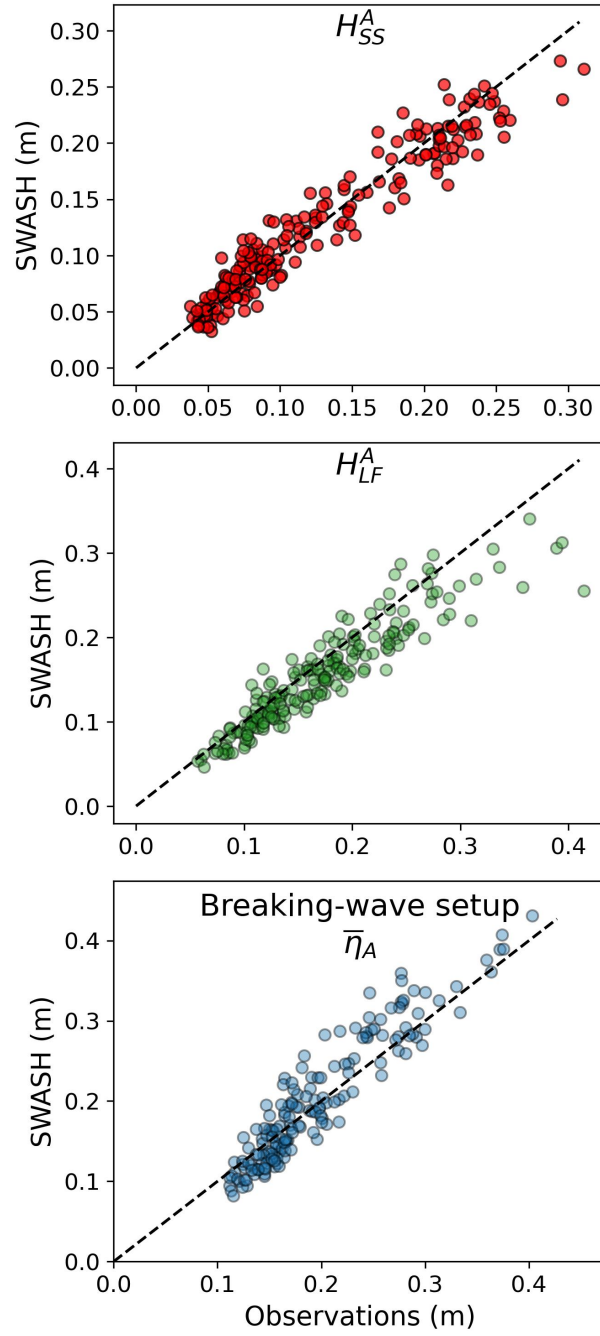


Figure 2.4. Model validation at the nearshore (sensor A) location of sea-swell significant wave height, low-frequency significant wave height, and breaking-wave setup.

suggest that the maximum nearshore H_{SS} can be estimated using a quadratic function of nearshore mean water depth, $\bar{h}_A$, (Figure 2.5) as

$$Max(H_{SS}^A) = 0.15\bar{h}_A^2 + 0.08\bar{h}_A \quad (m) \quad (2.6)$$

Above ~ 1.2 m mean water depth the scatter in shoreline SS wave heights increases, indicating greater dependence on offshore wave height, with only the highest waves reaching depth-limited breaking before the nearshore (sensor A) location. The coefficients in eq 3.4 are likely unique to our study site and sensitive to both reef bathymetry and friction. However, we hypothesize that the relationship is generalizable to similar reef-fringed coastlines.

How would the increase in shoreline SS wave energy with rising sea levels impact coastal flooding? As an indicator of flood risk, we consider the wave-driven component of total water level (TWL), defined as the still water level plus the 2% exceedance runup elevation, $R_{2\%}$, computed directly from the model output time series. At Faga‘itua, the model indicates that greater sea levels will increase $R_{2\%}$ (Figure 2.6). The rise in $R_{2\%}$ is dominated by the incident (sea-swell) swash (S_{inc}) component. Breaking-wave setup at the shoreline ($\bar{\eta}$) remains relatively constant. The low frequency swash (S_{LF}) component increases with rising sea level at a smaller rate than S_{inc} , suggesting that the LF energy is primarily set by nonlinear interactions of the shoaling swell. Uncertainty in modeled $R_{2\%}$ is not estimated, but Liu et al. (2021) found that laboratory measurements of $R_{2\%}$ on a fringing reef bathymetry matched SWASH estimates to within one standard deviation of model ensemble results.

The effects of SLR on coastal flood risk at Faga‘itua are twofold. Greater still water levels result in commensurate increases in wave-driven extreme runup ($R_{2\%}$), leading to elevated total water levels that flood the coastal road at our study site consistently once SLR reaches 1.4 m (Figure 2.7a), corresponding to relative SLR projections for 2100 under

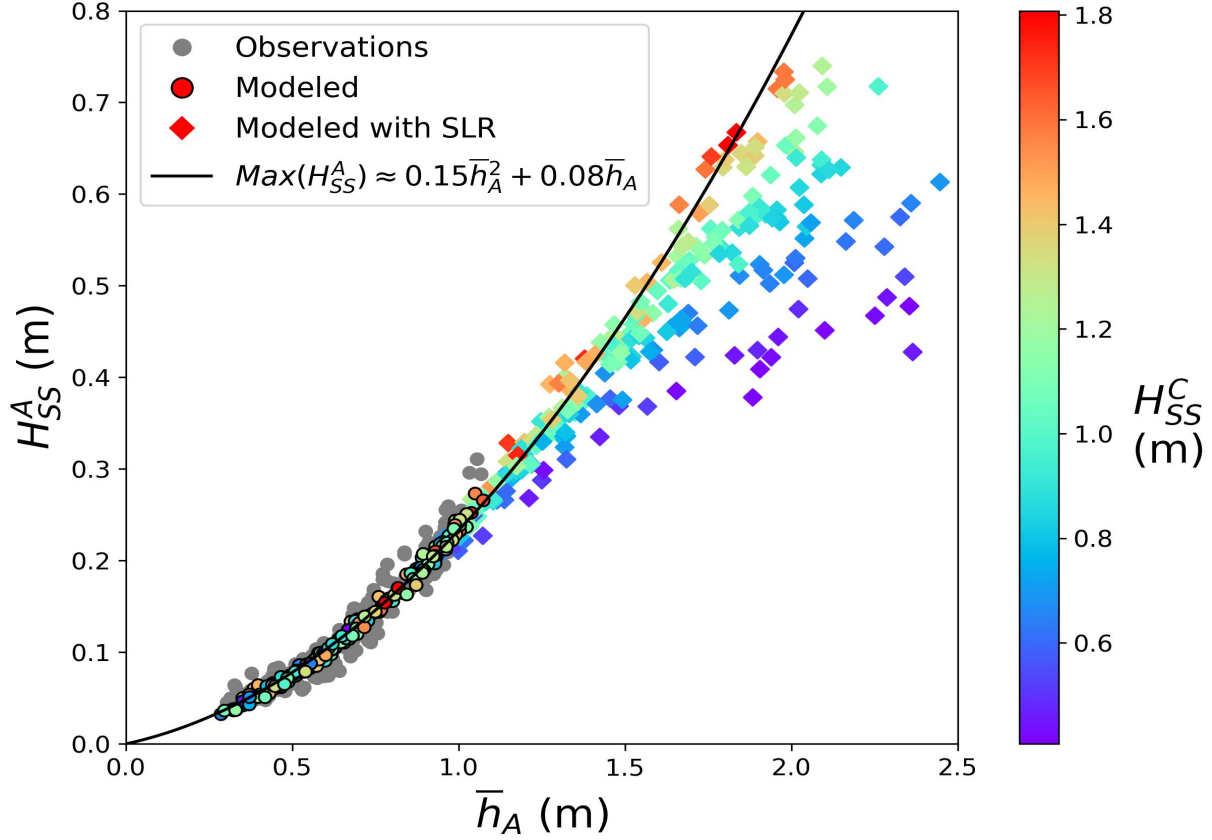


Figure 2.5. Modeled estimates of nearshore (sensor A) sea-swell significant wave height, H_{SS}^A , as a function of mean water depth nearshore, $\bar{h}_A$. 30-minute average observed (gray dots) and modeled estimates of the nearshore sea-swell significant wave height as a function of total mean water depth nearshore, colored by the observed sea-swell significant wave height on the reef face (sensor C), H_{SS}^C . We estimate maximum nearshore significant wave height using a quadratic function of total reef flat water level. The regression is computed using all model results run with observed water levels and model results for which $H_{SS}^C > 1.4$ m with added sea level.

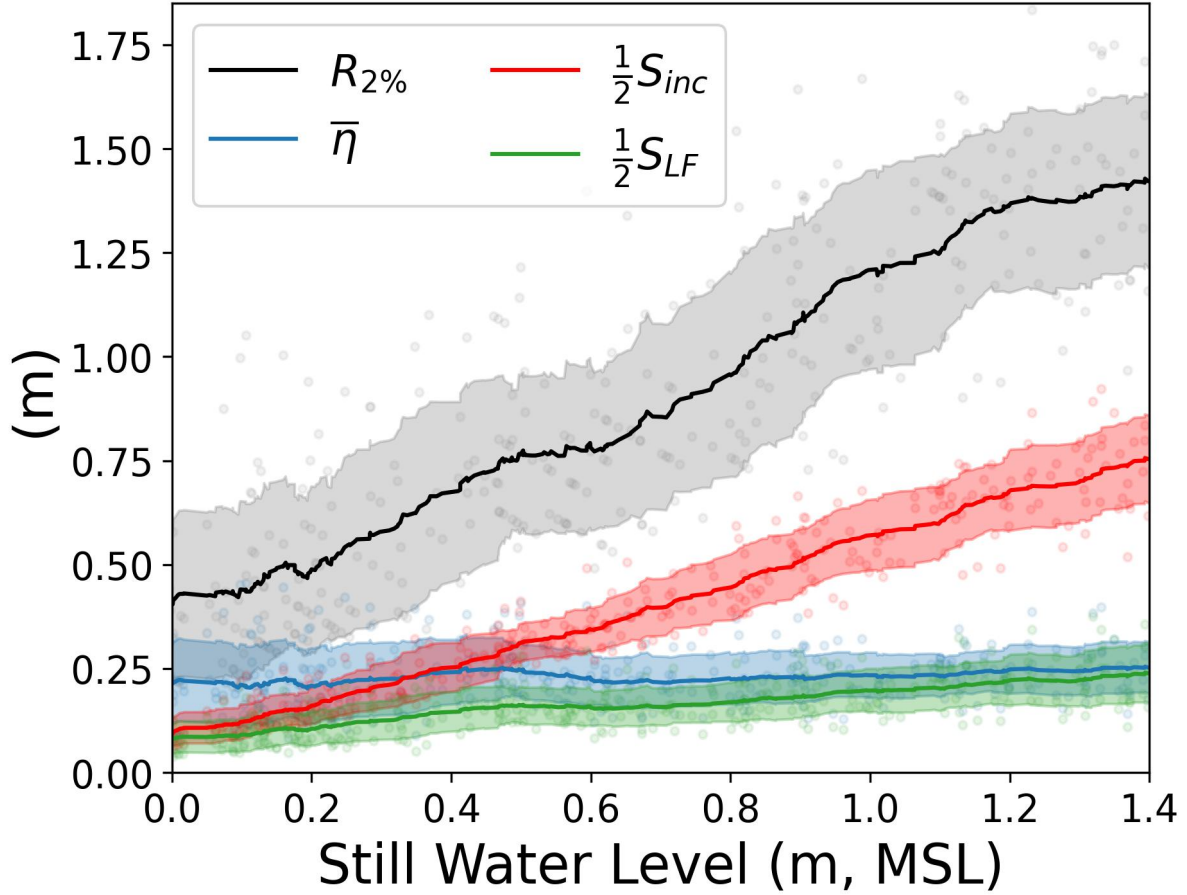


Figure 2.6. Modeled estimates of the 2% exceedance runup ($R_{2\%}$) and individual contributions from breaking-wave setup ($\bar{\eta}$), significant swash heights in the sea-swell (S_{inc}) and low-frequency (S_{LF}) bands, as a function of still water level. Individual model runs are shown as dots, the running means of each quantity are shown using solid lines, and the shading indicates a running ± 1 standard deviation. Above 1.4 m MSL the coastal road is often inundated and runup statistics are confounded by the curvature of the roadside.

the intermediate emissions scenario (Baizeau et al. 2023). We also estimate the number of days per year various vertical thresholds at the coastline are exceeded based on TWL (Figure 2.7b).

We next estimate historical nearshore SS significant wave heights and how they have evolved with changes in relative sea level at Tutuila from 1979 through May 2023 (Figure 2.8). Observed historical sea levels have, thus far, kept water levels at our observed Faga‘itua nearshore location below the 1.2 m threshold above which the model predicts nearshore SS wave height becomes increasingly dependent on offshore wave height. The mean water level is a combined estimate of sea level as measured by the NOAA Pago Pago tide gauge and the estimated breaking-wave setup. Our estimates of daily maximum nearshore SS significant wave height track closely with changes in relative sea level and show a marked increase as global sea levels have increased over several decades. Since 1979, the average of 0.32 m relative SLR has nearly doubled significant wave heights at the shoreline of Faga‘itua. El Niño events result in noticeably lower significant wave heights at the shoreline as regional water levels drop by 0.2-0.3 m (Widlansky et al. 2014). A marked increase in coastal wave energy has occurred since the magnitude 8.1 Samoa-Tonga earthquake doublet.

2.4 Discussion

Wave and water level observations at a fringing reef in Faga‘itua Bay on Tutuila island in American Samoa reveal that under current sea level, SS significant wave height at the shoreline is controlled by water depth over the reef, and the extreme wave-driven water levels are dominated by breaking-wave setup and LF motions. The greater the water level over the fringing reef, the greater the observed nearshore SS significant wave heights, consistent with depth-limited breaking. Deep water offshore wave heights determine the amount of breaking-wave setup, which increases the nearshore water level and therefore

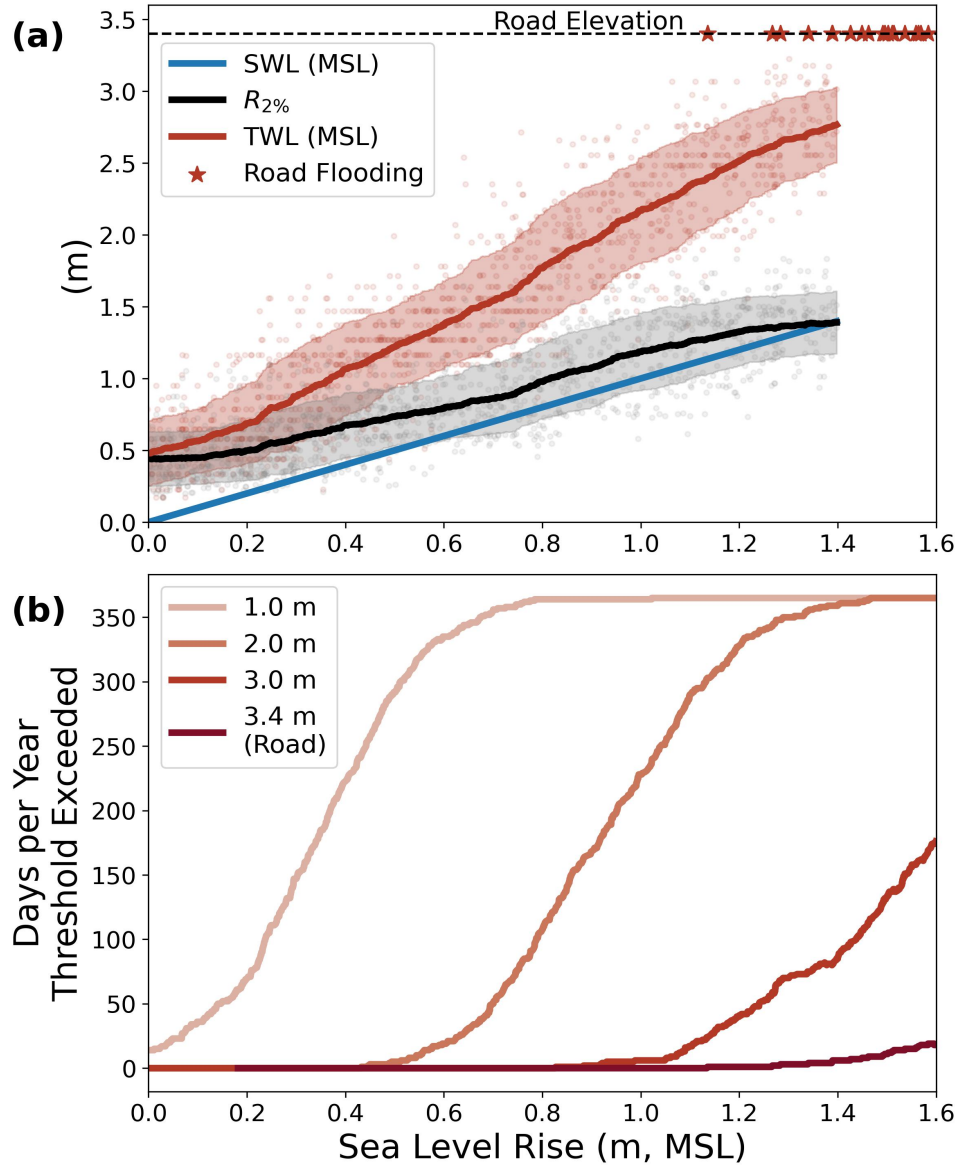


Figure 2.7. Modeled estimates of total water level (TWL), 2% exceedance runup ($R_{2\%}$), and days per year of vertical threshold exceedance as a function of sea level rise. (a) Model runs (associated with 4 different values of sea level rise) are shown as dots, the running means of each quantity are shown using solid lines, and the shading indicates a running ± 1 standard deviation. Above 1.4 m MSL the coastal road is often inundated and runup statistics are confounded by the curvature of the roadside. (b) Days per year the TWL exceeds vertical thresholds at the shoreline. For each value of sea level rise, the percentage of model runs clustered around this value for which TWL exceeds the threshold is converted to days in a year.

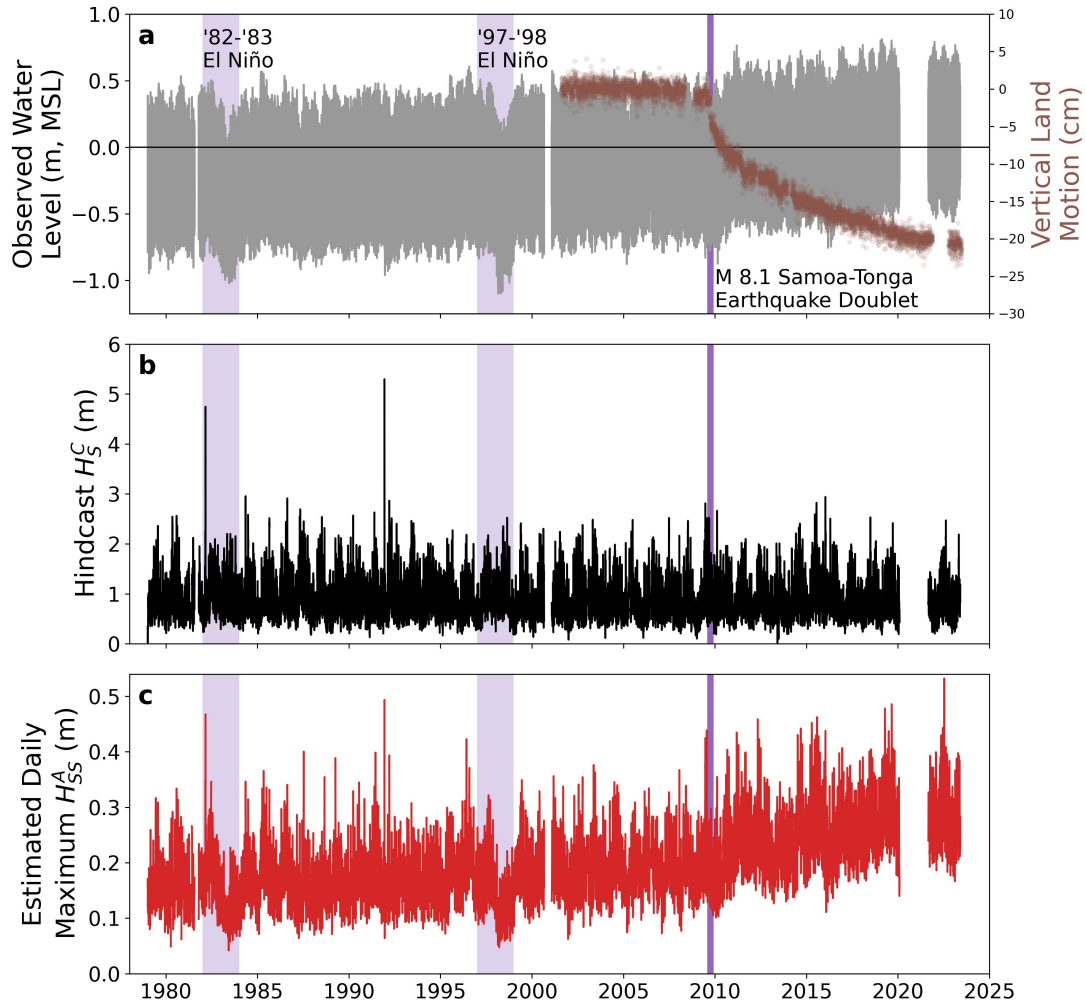


Figure 2.8. Historical sea level variability, hindcast reef face (sensor C) significant wave height, and daily maximum nearshore (sensor A) sea-swell significant wave height from 1979 through May 2023. (a) Observed sea level relative to mean sea level (MSL, tidal datum analysis period 01-Oct-2011 to 30-Sep-2019) at the Pago Pago tide gauge, courtesy of NOAA. We have highlighted the observed sea level depressions from the strong 1982-1983 and 1997-1998 El Niño events and indicated the magnitude 8.1 Samoa-Tonga Earthquake doublet on September 29, 2009. To highlight the rapid land subsidence following the 2009 earthquakes, vertical land motion from 2001 to present is shown on the right-hand vertical axis, relative to the pre-2009 mean; data courtesy of the Nevada Geodetic Laboratory (Blewitt et al. 2018). (b) Bias-corrected hindcast reef face (sensor C) significant wave height using hindcasts from Smith et al. (2020) and a linear spectral refraction model. (c) Estimated daily maximum nearshore (sensor A) Faga‘itua sea-swell significant wave height based on the nearshore water depth.

increases the nearshore SS wave height.

To assess how changes in relative sea level affect shoreline SS wave heights, we use SWASH, a phase-resolving nonhydrostatic numerical model applied at a cross-reef transect in Faga'itua Bay. Waves are transformed over the fringing reef with past, present, and future water levels. We find that the model predicts that the maximum nearshore SS significant wave height for a given water depth increases quadratically with water depth. As water levels exceed ~ 1.2 m mean water depth, the dependence on offshore wave height increases as smaller waves are able to propagate across the reef without breaking.

Over the past 50 years, rising sea levels have contributed significantly to amplified shoreline wave energy at Faga'itua Bay. From 1979 through September 2009, we estimate that the daily maximum nearshore SS significant wave height increased at a rate of 0.01 m/decade for an SLR of 0.04 m/decade; from October 2009 through May 2023, that rate jumped to 0.06 m/decade for an SLR of 0.16 m/decade. The effects of land subsidence associated with the earthquakes, most recently measured at 6 to 9 mm/yr (Huang et al. 2022), are expected to continue for several decades (Han et al. 2019).

Modeling results suggest that the destructive potential of swells incident on fringing reef shorelines of American Samoa will increase as relative sea level increases. The extreme water level becomes dominated by SS wave heights as some SS waves cease to break at the reef crest. In addition to the flood risk associated with relative sea level increases projected for American Samoa, our results raise concerns about the flood risk associated with the increase in the 2% exceedance shoreline runup, and a growing dominance of SS energy. Given the proximity of built infrastructure to the shoreline at American Samoa, the combined impacts of increased waves and water levels pose a considerable challenge for coastal defense. For example, we use the SWASH results to illustrate how rising waves and water levels will impact the maximum wave pressure on a vertical breakwater (Figure 2.9). We use the formulation of Goda (1974) for calculating the maximum wave pressure on a hypothetical vertical breakwater built nearshore (at sensor A's location) as a function

of sea level, assuming normal incidence. The maximum wave pressure, p_1 , is a function of the significant wave height at A, H_S^A , the water depth, h , and the design wave wavelength, L , through the following adapted formulae:

$$p_1 = 1.8\rho g H_S^A \left(\alpha_1 + \frac{2h}{1.8H_S^A} \right) \quad (2.7)$$

$$\alpha_1 = 0.6 + \frac{1}{2} \left(\frac{4h/L}{\sinh(4\pi h/L)} \right)^2 \quad (2.8)$$

where ρ is the density of sea water and g is the gravitational acceleration. Our model suggests that as the nearshore water depth increases, the design wave height increases and therefore the maximum wave pressure on the vertical wall increases. Despite the increase in scatter of the nearshore significant wave height with increasing water depth, eq 2.7 predicts a near-linear increase in the maximum wave pressure.

Detailed analysis of future flooding is forthcoming and will incorporate the full suite of relative sea level projections developed for the American Samoa Sea Level Rise Viewer by Baizeau et al. (2023), estimates of future wave climatology, measured reef growth and accretion rates, and two-dimensional numerical modeling. This study assumes a fixed reef bathymetry, which we hope will serve as a possible worst-case scenario when it comes to reef response to SLR. Reef accretion and growth relative to rising sea level will limit increases in shoreline wave energy. Historical reef accretion rates inferred from cores taken at other reefs fringing Tutuila suggest that accretion rates have varied and kept pace with periods of rapid SLR during the Holocene. However, the species primarily responsible for this reef accretion appears to have died off in the past century, in part due to coastal construction in the 1940s (Birkeland et al. 2021), motivating current reef growth and accretion study. Modeling 2-dimensional effects of alongshore reef variation will increase confidence in model results and spatial coverage of the projections, but we believe that the general results presented here will remain relevant. This study does not attempt to

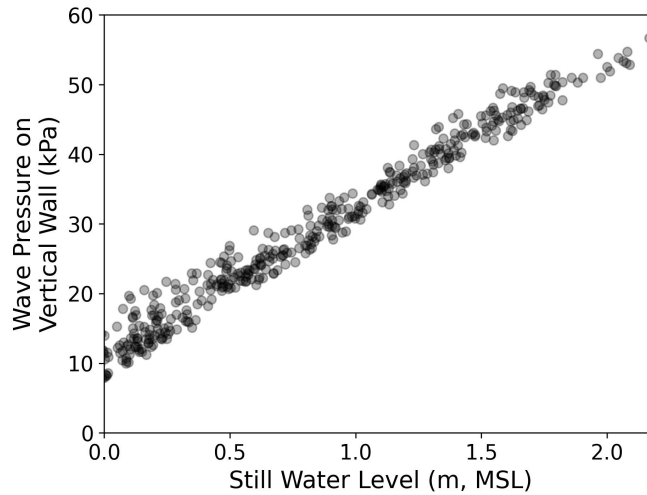


Figure 2.9. Modeled calculations of the maximum wave pressure on a hypothetical vertical breakwater constructed nearshore (sensor A), using the formulation from Goda (1974), as a function of still water level.

predict the timing of elevated water levels relative to the reef top but lays the groundwork for projections of nearshore SS wave energy once those estimates are constrained.

American Samoa’s relative sea level continues to rise, increasing the risk to coastal infrastructure from damaging wave events. The majority of American Samoa’s housing and infrastructure will face significant threats from the relative SLR and associated increases in nearshore SS wave energy. Coastal erosion rates have increased dramatically due to rapid relative SLR (Herrmann and Keene 2016), causing a cascade of deleterious impacts: loss of most sandy beaches around the island, loss of coastal land, damage to main roads, and the failures of seawalls that have hardened much of the coastline of Tutuila. Current passive flood modeling estimates based on relative sea level projections alone predict that much of American Samoa’s most critical infrastructure, including the only international airport and much of the main coastal road, will be threatened by 2100 under the intermediate emissions scenario resulting in 1.4 m relative SLR. Our model results suggest that the impacts under this amount of relative SLR will be greater because these estimates have not taken into account the increase in potentially destructive SS wave energy at the shoreline.

ACKNOWLEDGEMENTS

Support for this study was provided by the U.S. Army Corps of Engineers (W912HZ1920020) and the U.S. Department of the Interior through the Pacific Islands Climate Adaptation Science Center (G15AP00140 and G21AC10399). We thank Mika Siegelman, Mele Johnson, Derek Young, and Christina Comfort for deploying and recovering the instruments used in the 2017 field study of Tutuila Island. We thank Stephen White, Mike Aslaksen, and Dennis Hall from NOAA for providing the preliminary topobathy digital elevation model. At the time of writing this DEM had not yet been through the full NOAA quality assurance process and approval. We assume liability of any further application of the data and errors present. This study was informed by ongoing sea level adaptation work in American Samoa led by Kelley Anderson Tagarino, the University of Hawaii Sea Grant Extension specialist.

Chapter 2, in full, is a reprint of the material as it appears in Scientific Reports 2024. Barnes, Austin T.; Becker, Janet M.; Tagarino, Kelley A.; O'Reilly, William C.; Siegelman, Mika; Thompson, Philip R.; Merrifield, Mark A., Springer Nature, 2024. The dissertation author was the primary investigator and author of this paper.

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Chapter 3

Satellite-Derived Shoreline Analysis of O‘ahu: Investigating Drivers of Interannual Beach Changes

3.1 Introduction to Hawai‘i’s Beaches: Dynamic Systems at Risk

Understanding and monitoring Hawai‘i’s beaches is critical for coastal hazard assessment, sea level rise (SLR) impact mitigation, cultural preservation, environmental management, and Hawai‘i’s tourism economy. This study utilizes multi-year satellite-derived shoreline (SDS) data to analyze interannual beach changes across O‘ahu for patterns and insights into island-wide beach dynamics and their driving mechanisms. Beaches in Hawai‘i serve as vital protective buffers against extreme ocean conditions, including high tides, persistent non-tidal sea level anomalies (SLA), large swell and storm waves, and combinations of other oceanic variability. They form a critical first line of defense, absorbing and dissipating wave energy and preventing potential damage to coastal infrastructure and communities. Beyond their protective function, beaches hold immense cultural significance, creating essential connections between Hawai‘i’s people and the ocean that has shaped island life for centuries.

3.1.1 Multi-Temporal Beach Dynamics and Drivers

Coastal change in Hawai‘i operates across multiple temporal scales, each with distinct drivers and patterns. Episodic events lasting hour to days, such as large storms and swells, can cause dramatic short-term changes to beach morphology (e.g., Dail et al. 2000). Shifts in predominant wave direction and energy between summer and winter months produce relatively predictable cycles of beach accretion and erosion, as demonstrated in monitoring studies of beaches such as Kailua Beach (Norcross et al. 2002) and Kahaloa (Royal Hawaiian) Beach in Waikīkī (Mikkelsen et al. 2022; McDonald et al. 2022). Long-term trends spanning decades reveal the cumulative effects of SLR, changes in sediment supply, and human development along the coastline (Romine et al. 2013; Fletcher et al. 2012). Changes from year to year, occurring at timescales between seasonal and decadal, remain less thoroughly studied along much of O‘ahu, Hawai‘i, despite their importance for assessing beach health and resilience. Understanding these interannual variations and their drivers will provide crucial links between subannual processes and decadal trends so that we may better anticipate our shorelines’ future.

O‘ahu’s beaches experience a diverse and seasonally variable wave climate that influences shoreline positions and sediment transport patterns differently across the island’s coastlines, with four distinct swell regimes creating location-specific and temporally variable responses depending on the coastline, beach orientation, coastal morphology, and season (Figure 3.1). From October through March, boreal winter storms in the North Pacific generate powerful north and northwest swells that directly impact O‘ahu’s north shore and often have significant influence on the west and east shores as they refract around the island’s bathymetry (Li et al. 2016). These winter swells produce the largest wave events experienced on the island with annually recurring significant wave heights of nearly 8 m (Vitousek and Fletcher 2008). Consistent northeasterly and easterly trade winds and waves influence the coasts year-round, particularly the east shore of O‘ahu, with

greatest intensity during summer months. Modest southern swells generated by year-round Southern Hemisphere Westerlies and boreal summer southern mid-latitude cyclones break along O‘ahu’s south and west shores, most often and largest from April through September (Li et al. 2016). Subtropical cyclones and “Kona storms” can produce significant local waves for all shores, most often during winter months and for south and west shores (McDonald et al. 2022). Neighboring islands only partially shadow O‘ahu from distant swell generation, most notably from the west-northwest and southeast. Cyclical erosion and accretion patterns resulting from this wave climate vary significantly between windward (east), leeward (west), and north-facing shores.

The dynamic nature of Hawai‘i’s beaches involves complex interactions with offshore coral reef ecosystems. These reefs, which have developed over thousands of years, play a crucial role in beach formation and maintenance through their interaction with waves and water levels. The relationship between beach morphology and reef structure creates coastal systems that respond to environmental forcings in ways that are often different from continental coastlines (Storlazzi et al. 2004). For example, the hydrodynamics of Hawaiian reef systems can be dominated by wave-driven circulation (Inman et al. 1964). Reef morphology plays a crucial role, with the width and depth of the reef flat affecting flow velocities and residence times (Lowe et al. 2009). Water level variations, whether from tides, breaking-wave setup, persistent SLA, or long-term SLR, can significantly influence wave propagation and water circulation over reefs (Storlazzi et al. 2004). Higher water levels generally allow larger sea-swell waves to propagate across the reef with less energy dissipation (e.g., Barnes et al. 2024). In Kāne‘ohe Bay, wave heights over the fringing reef flats are strongly correlated with tidal level, with the highest waves occurring during high tide due to reduced wave breaking over the shallow reef crest and reduced frictional dissipation over the reef flat (Lowe et al. 2009). Breaking waves at the reef crests or on the reef flats establish a pressure gradient that drives flow across the reef, alongshore, and back out through deeper channels or gaps in the reef, mobilizing sediment

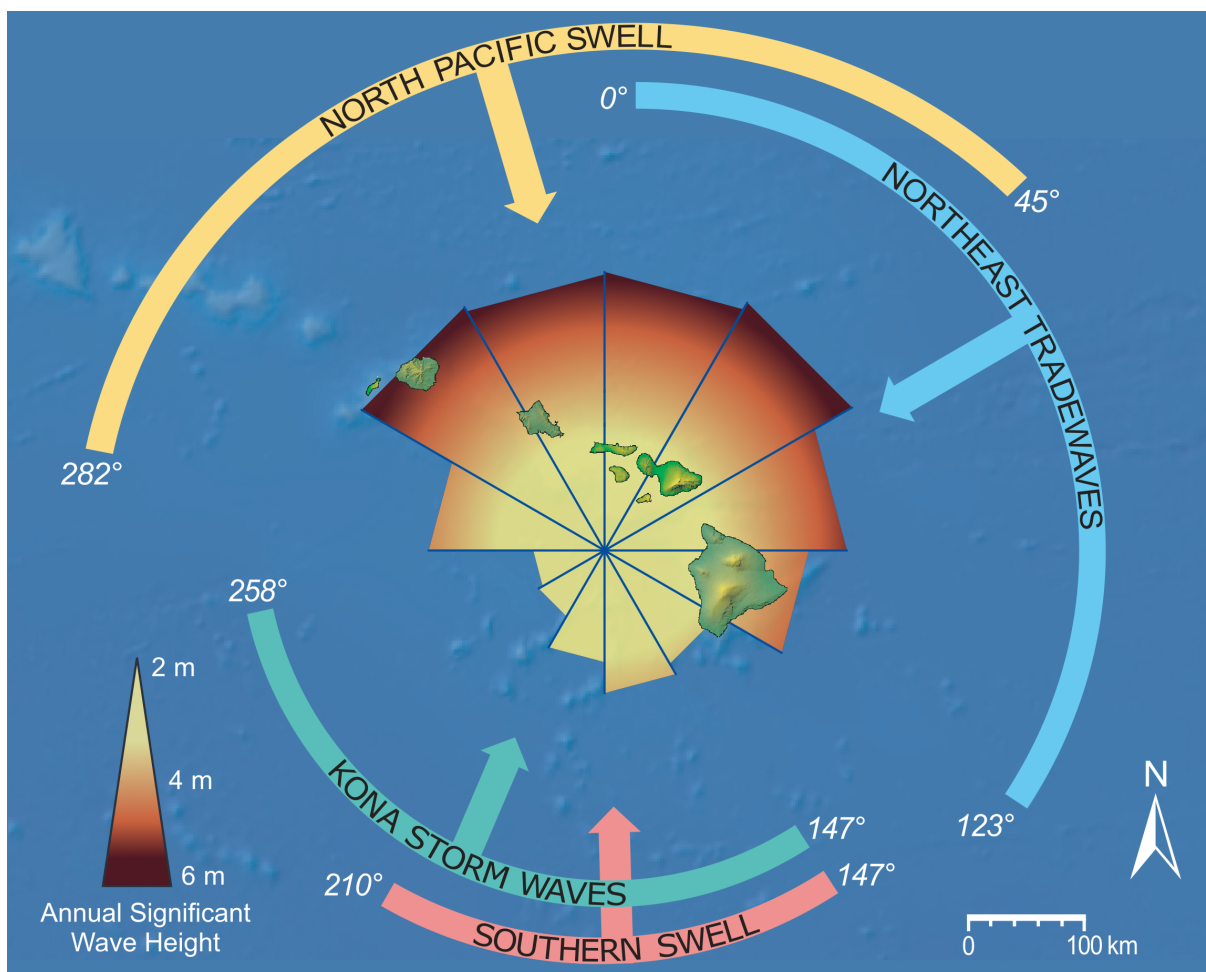


Figure 3.1. Hawaiian Island wave climatology. North Pacific swell is largest October through March and impacts north, east, and west shores. Persistent northeasterly trade winds generate tradewaves year round, strongest in boreal summers. Southern swell and Kona storms generate modest waves that primarily impact the south and west shores. Neighboring islands only partially shadow O‘ahu from distant swell generation. Reproduced with permission from McDonald et al. (2022). Copyright 2008 Charles H. Fletcher.

on the reef flats and alongshore and depositing sand in the channels where flow velocities decrease (Conger 2005). At four reef-fringed beaches with different oceanographic forcings (Kailua and Waikīkī, O‘ahu; Kā‘anapali and Kīhei, Maui), longshore sediment transport dominated the seasonal beach patterns (Norcross et al. 2003). Rather than following the conceptual model of predominantly cross-shore transport through which large wave events erode the subaerial beach, depositing this sand in offshore bars until recovery conditions reconnect the sediment onshore (e.g., Lee et al. 1995), these findings suggest that for many of Hawai‘i’s beaches, longshore transport driven by reef flows could be of primary importance. By contrast, Waimea Bay on the north shore of O‘ahu is an embayed beach relatively unprotected by reef except from extraordinarily large swells. Here, Dail et al. (2000) observed energetic wave events move sand cross-shore onto an offshore sand field with subsequent periods of recovery during weaker wave conditions.

The complex reef-beach systems are not all operating as closed littoral cells, and sediment leakage occurs through various pathways. The open nature of Hawai‘i’s beach systems contributes to the vulnerability of coastal areas as sand can be permanently lost from the active beach system. Studies at Kailua Beach, on O‘ahu’s east shore, indicate that most modern beach sand was created hundreds to thousands of years ago, suggesting that modern sediment regeneration is a small contribution to the island’s sand supply (Harney et al. 2000; Harney and Fletcher 2003; Resig 2004). As a result, persistent beach erosion trends represent a significant and growing threat to O‘ahu’s coastal areas. Recent projections indicate that 81% of O‘ahu’s beaches could lose a substantial portion of their sand by the end of the century, with 40% of this loss occurring by 2030 (Moskvichev et al. 2025). These revised forecasts suggest more severe and rapid erosion than previous studies had indicated, predominantly through a combination of recession as a response to SLR (Bruun 1962) and other long term trends less well understood (Romine et al. 2013). Bitterwolf et al. (2024) found that while fringing reefs are extremely effective at protecting shorelines from individual storms, beaches in Hawai‘i fronted by reefs have eroded up to

twice as much as beaches without reefs, suggesting greater disequilibrium under SLR for reef-protected beaches. Additionally, anthropogenic interventions such as coastal armoring lead to beach loss (Tavares et al. 2020). Given how complex the beach systems of O‘ahu are, we seek to use SDS to tease out significant interannual patterns of variability and suggest mechanisms that have implications for future erosion forecasts.

3.1.2 Satellite-Derived Shoreline Advancements

Historical beach monitoring in Hawai‘i has relied heavily on field-based approaches, including topographic surveys, aerial and drone-based photogrammetry and LiDAR. While these methods provide high-accuracy data, they are labor-intensive, costly, and typically limited to either specific coastal segments or intermittent (years apart) comprehensive island-wide assessments. The advent of satellite remote sensing has revolutionized coastal monitoring capabilities, enabling more frequent and spatially extensive observations. Satellite-derived shorelines (SDS) have been used for detection and analysis of shoreline changes at the seasonal, interannual, and decadal time scales (Vos et al. 2019), including Pacific Basin-wide responses to the El Niño Southern Oscillation (ENSO) (Vos et al. 2023).

Since the late 1990s, satellite imagery of Hawai‘i’s coastlines has progressed from seasonal coverage to sub-monthly frequency. The increase in temporal density of observations allows for the detection of patterns in beach width over time and length scales that were previously difficult to capture. Despite their advantages, SDS present unique challenges that require careful methodological consideration. Early generations of satellites have relatively coarse horizontal resolution (e.g., 30 meters for Landsat, 10 meters for Sentinel-2), which impose limitations for monitoring Hawai‘i’s often narrow and steep beaches. More recent satellite platforms like PlanetScope offer higher resolution (approximately 3 meters) starting in 2017, providing improved estimates of instantaneous waterlines (Moskvichev et al. 2025). However, these instantaneous waterlines capture complex combinations of tidal variations, SLA, wave runup, and wave setup that must be accounted for when

deriving meaningful shoreline positions (Vos et al. 2019).

CoastSat offers a publicly available dataset of SDS for a limited number of O‘ahu beaches with transects spaced roughly 100 m apart. Moskvichev et al. (2025) significantly increased the spatial coverage of SDS by implementing 20-m spaced transects at all of O‘ahu’s sandy shorelines. They implemented CoSMoS-COAST to project long-term shoreline change by including longshore transport, SLR-driven recession (Bruunian, based solely on intermediate SLR projections), wave-driven cross-shore transport, and a residual linear trend term to capture the long term rates from previous shoreline analyses and other processes (Vitousek et al. 2017).

While numerous studies have examined individual beaches or limited coastal segments in Hawai‘i, few have analyzed island-wide beach behavior at interannual timescales. The recent availability of consistent, multi-decade satellite records provides an unprecedented opportunity to investigate patterns and drivers of year-to-year beach changes across O‘ahu’s diverse shorelines. Understanding these interannual patterns has significant implications for beach management, setback policies, and flood predictions. Moskvichev et al. (2025) predict that dynamic, wave-driven processes (longshore and cross-shore transport) account for approximately 30% of projected shoreline change between 2023 and 2100, with Bruunian recession due to SLR and other residual processes dominating long-term trends. However, changes to O‘ahu’s shorelines due to wave-driven processes are based on the assumption that these processes will continue to operate in the same way in the future, without accounting for possible effects of SLR and other variability.

The present study leverages SDS data to analyze interannual beach width changes across three of O‘ahu’s four shorelines (north, west, and east) from October 1999 through September 2022. By examining year-to-year patterns in beach width and correlating these with potential driving factors such as wave climate variations and SLA, this research seeks to improve understanding of the mechanisms controlling interannual beach dynamics. This knowledge will enhance the capacity to predict future beach conditions and inform

adaptive management strategies in the face of accelerating climate change impacts on Hawai‘i’s coastlines.

3.2 Observations and Methodological Approach

3.2.1 Study Area and Shoreline Data Exclusion Criteria

This study focuses on sandy beaches along O‘ahu’s north, east, and west shores monitored and modeled by Moskvichev et al. (2025). We exclude littoral cells from our analysis based on several criteria to maximize the ratio of meaningful signal to noise: those that are narrow (<10 m cross-shore at their widest point), short (<100 m alongshore), heavily vegetated, shadowed, or perched beaches with persistent beachrock exposure that can confuse automated shoreline detection, or heavily modified by human interventions that influence observed beach behavior (e.g., recurring beach nourishments, seasonal beach bulldozing, etc.). We exclude the south shore of O‘ahu due to many of its beaches’ additional complexities. For example, human modifications — including the 2016 and 2021 Kahaloa Beach nourishments and the 2016 ‘Ewa Beach groin construction — introduce non-natural variability that obscures interannual signals. We therefore reduced the 112 littoral cells specified for O‘ahu by Moskvichev et al. (2025) down to 47 for our analysis (Figure 3.2). Several south shore beaches are still viable for future analysis.

3.2.2 Satellite-Derived Shoreline Data and Processing

We use the comprehensive SDS dataset (October 1999 through September 2022) from Moskvichev et al. (2025) to analyze interannual beach width changes around O‘ahu. To maximize consistency, we use only the beach widths derived from the CoastSat framework, including Landsat and Sentinel-2 satellite imagery. We exclude Planet satellite images to remove any sampling biases introduced in 2017 when Planet images are available that may not be accounted for in the bias-corrections applied by Moskvichev et al. (2025).

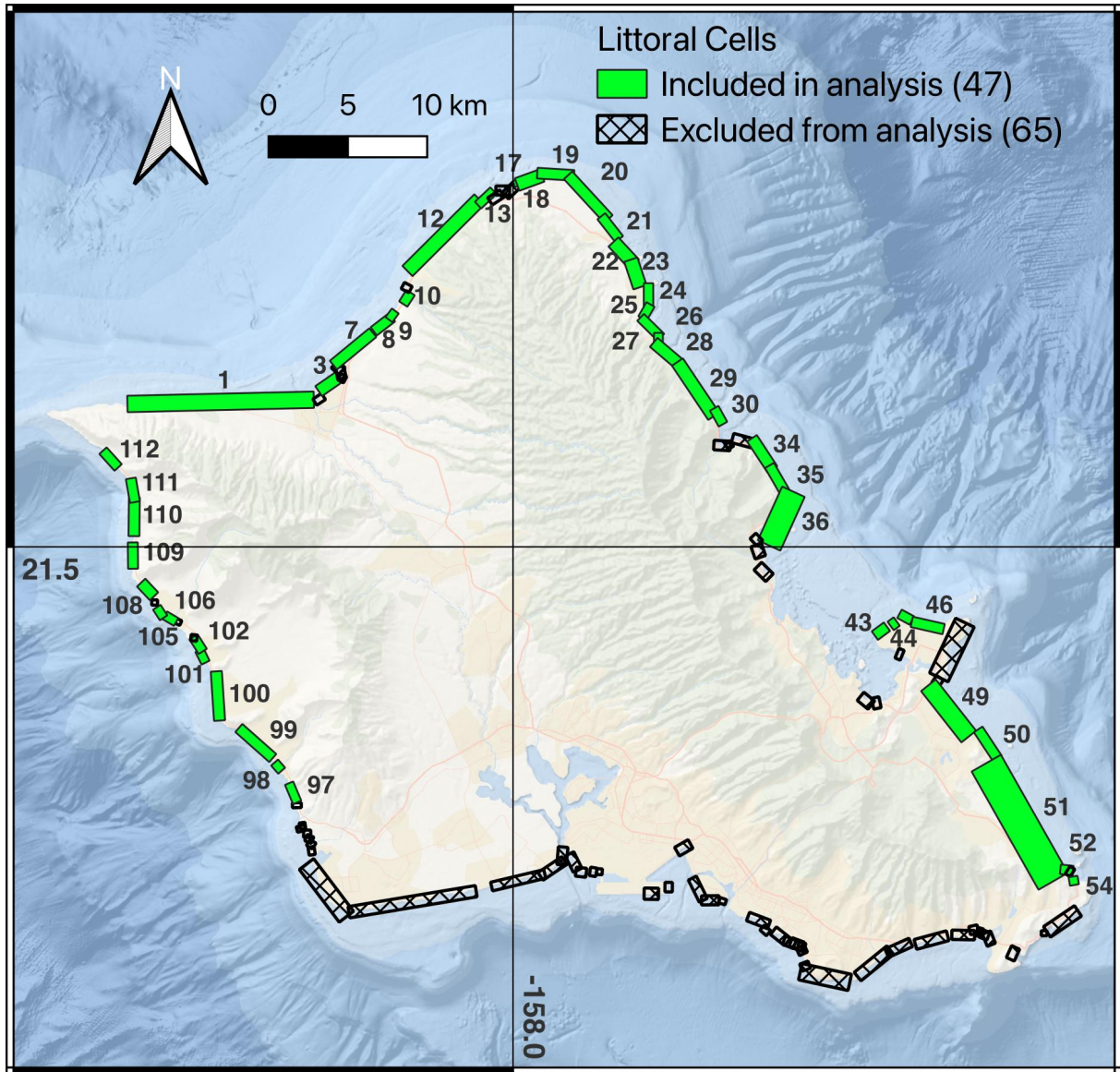


Figure 3.2. O‘ahu littoral cells from Moskvichev et al. (2025) used for interannual analysis. Green filled boxes indicate the 47 cells used in our analysis. Black hatched boxes indicate the 65 cells excluded from analysis due to narrow beach width (<10 m cross-shore at widest point), short length (<100 m alongshore), or characteristics that may confuse automated shoreline detection. We entirely exclude from our analysis the south shore of O‘ahu due to many of its beaches’ additional complexities. Basemap from ESRI.

Annual average beach width anomalies derived from CoastSat and Planet are nevertheless consistent.

To quantify beach width changes, Moskvichev et al. (2025) established shore-normal transects at approximately 20-m intervals. At each transect, they measured the distance between a fixed landward reference point and the derived mean sea level contour for each available satellite observation. Water level corrections for tides using a global tide model were made in Moskvichev et al. (2025). We apply an additional analogous correction for daily SLA using the average value of daily mean SLA measured at the Honolulu (UHSLC ID 57) and Moku o Lo'e (UHSLC ID 61) tide gauges (Caldwell et al. 2015) for a given satellite observation date. We refer you to Moskvichev et al. (2025) for additional details on their shoreline position algorithms.

Following O'Reilly et al. (2025), we calculate seasonally-weighted, annual average beach width anomalies at each transect by “beach year” (October - September) and report these values centered on January 1 of every year. To mitigate uneven temporal sampling (due, for example, to seasonal cloud cover) that can lead to seasonal biases (i.e., data-dense seasons disproportionately influencing annual means), we first calculate monthly mean shoreline positions, then seasonal (i.e., quarterly) averages from the monthly means, and finally annual beach year averages from quarterly means. At each transect, we compute the annual average beach width anomalies by subtracting the 2000-2022 mean width. Through comparisons with in situ surveys, O'Reilly et al. (2025) found that annual averages minimized SDS errors due to unresolved wave runup at Southern California beaches, and we assume, in the absence of additional in situ survey data, the same is true for Hawai'i SDS. The annual beach width anomalies are further spatially averaged by shoreline (Figure 3.3). The combination of annual and spatial averaging minimizes seasonal beach rotations due to alongshore transport.

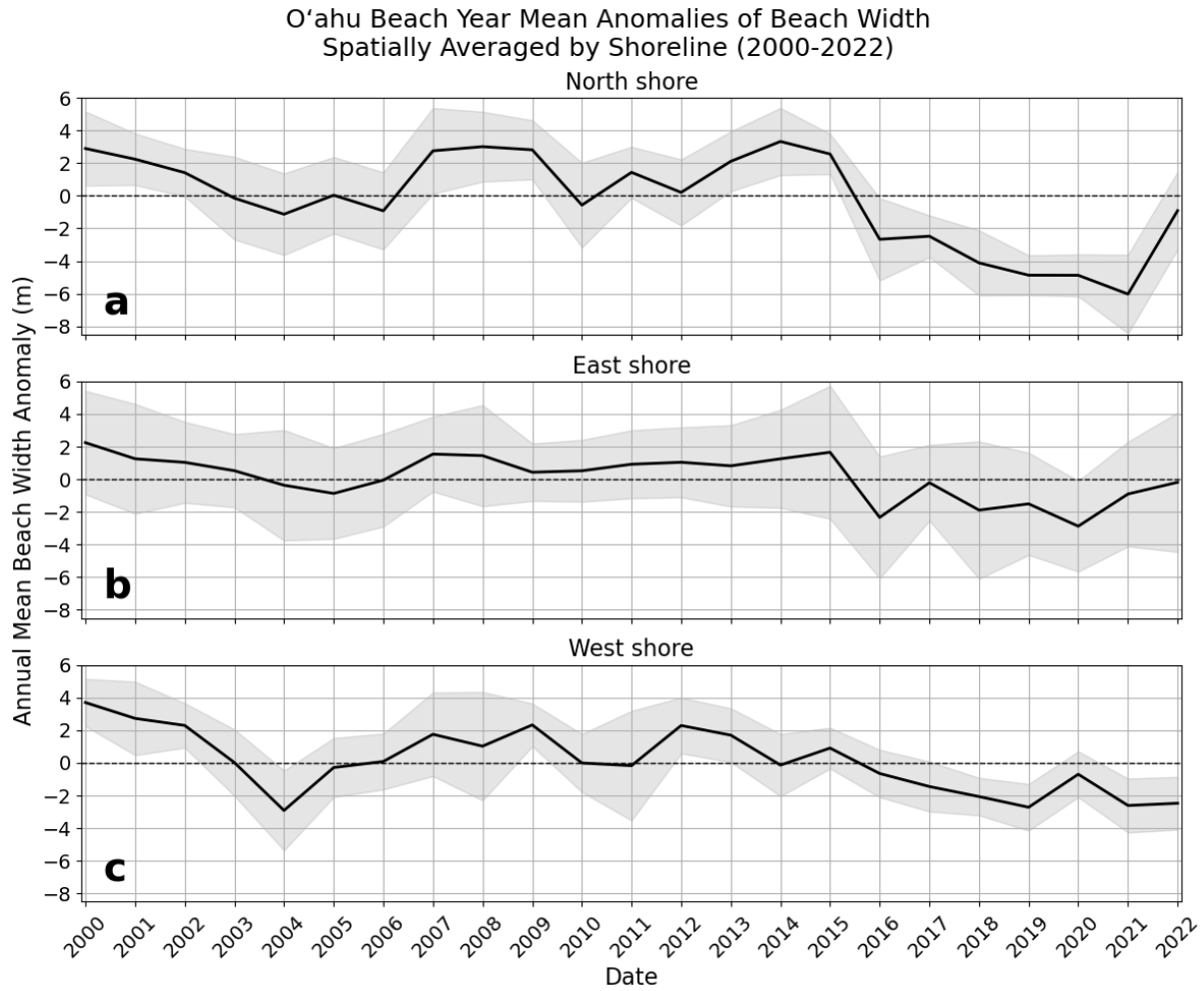


Figure 3.3. Mean anomalies of beach width, spatially averaged by shoreline for the (a) north, (b) east, and (c) west shores of O'ahu from beach years 2000 through 2022 (solid black lines). ± 1 standard deviations about the mean (i.e., standard deviation of the spatial average as a function of time) are shown in the gray shading.

3.2.3 Potential Beach Change Driver Data

We include in our analysis of potential beach change drivers the annual beach year average anomalies (henceforth “annual anomalies”) of mean sea level, wave power, wave direction, precipitation, wind speed and wind direction (Figure 3.4). We compute annual anomalies of mean sea level with the same time series used for sea level corrections of shorelines. We average daily mean sea level measured at the Honolulu (UHSLC ID 57) and Moku o Lo’e (UHSLC ID 61) tide gauges (Caldwell et al. 2015) for the study period (RMSE of the two time series = 0.0196 m, $r^2=0.93$), and compute its annual anomaly.

Wave power and wave direction are differentiated for the three distinct shorelines due to their distinct wave climates (Figure 3.1). Hourly observations of significant wave height, H_s , peak period, T_p , and peak wave direction for the north shore (Waimea Bay buoy, CDIP station 106, available from Dec. 2001 onwards) and east shore (Mōkapu Point buoy, CDIP station 098, available from Aug. 2000 onwards) were furnished by the Coastal Data Information Program, Integrative Oceanography Division, operated by the Scripps Institution of Oceanography. The Waimea and Mōkapu buoys are maintained by PacIOOS. Data missing from the beginning of the study period and intermittent gaps were backfilled using the nearest hourly ERA5 reanalysis data on single levels, ocean-wave fields, available from 1940 through the study period at 0.5 degree grid resolution (Hersbach et al. 2023). We apply a mean bias correction to the ERA5 H_s (Waimea $r^2 = 0.83$, ERA5 offset = +0.45 m; Mōkapu $r^2 = 0.79$, ERA5 offset = +0.06 m), and approximate wave power, P , using eq 3.1 and 3.2, assuming a JONSWAP spectrum, following Tucker and Pitt (2001):

$$P \approx 0.49 * H_s^2 * T_E \quad (3.1)$$

$$T_E \approx 0.9T_p \quad (3.2)$$

Estimates of wave power do not differ significantly when we use buoy-derived, directional

wave energy spectra to approximate T_E directly. Wave observations for the west shore (Barbers Point, Kalaeloa buoy, CDIP station 238, available from May 2018 onwards) are limited; we instead used monthly wave power derived from ESTELA (Pérez et al. 2014) forced by the CAWCR wave hindcast (Durrant et al. 2019) for a point offshore of the Wai‘anae coast (21.424114 N, -158.198353 W). No bias corrections are applied to the Wai‘anae wave power. We derive wave direction on the west shore from the nearest hourly ERA5 reanalysis data.

We compute the annual anomalies of an hourly total water level (TWL) hindcast for Rock Piles beach on the north shore of O‘ahu to analyze its effect on the beach width of the littoral cell containing this beach (shoreline 12). Following the total extreme water levels of Merrifield et al. (2014), the hourly TWL is estimated as a combination of the observed still water level and the 2% exceedance level of sea surface elevation near the shoreline. Empirical relationships between Waimea buoy H_s , observed sea level, and the 2% exceedance nearshore sea surface elevation (a combination of wave setup, infragravity wave runup, and sea-swell wave runup components) at Rock Piles provided by the Pacific Islands Ocean Observing System (PacIOOS) were driven by our hourly record of Waimea H_s and a sea level hindcast at Hale‘iwa Harbor. Hourly sea level measured at the Hale‘iwa tide gauge (UHSLC ID 422) is only available from March 2023 through March 2025. We subtract daily SLA from this hourly record, decompose the remaining record into its major tidal constituents, and reconstruct an hourly tidal record during our study period by using the open-source Python package UTide v1.0 (Codiga 2011) and adding the daily SLA.

Daily observations of cumulative precipitation from three rain gauges provided by the U.S. Geological Survey (USGS) are used as proxies for regional rainfall. We used Pūpūkea Rd (station 213608158011101) for the north shore, Kahana (station 213237157530701) for the east shore, and Mākaha for the west shore (station 213016158105901). Intermittent gaps in data were treated as no rainfall when we computed annual anomalies. We computed annual anomalies from hourly estimates of 10 m wind

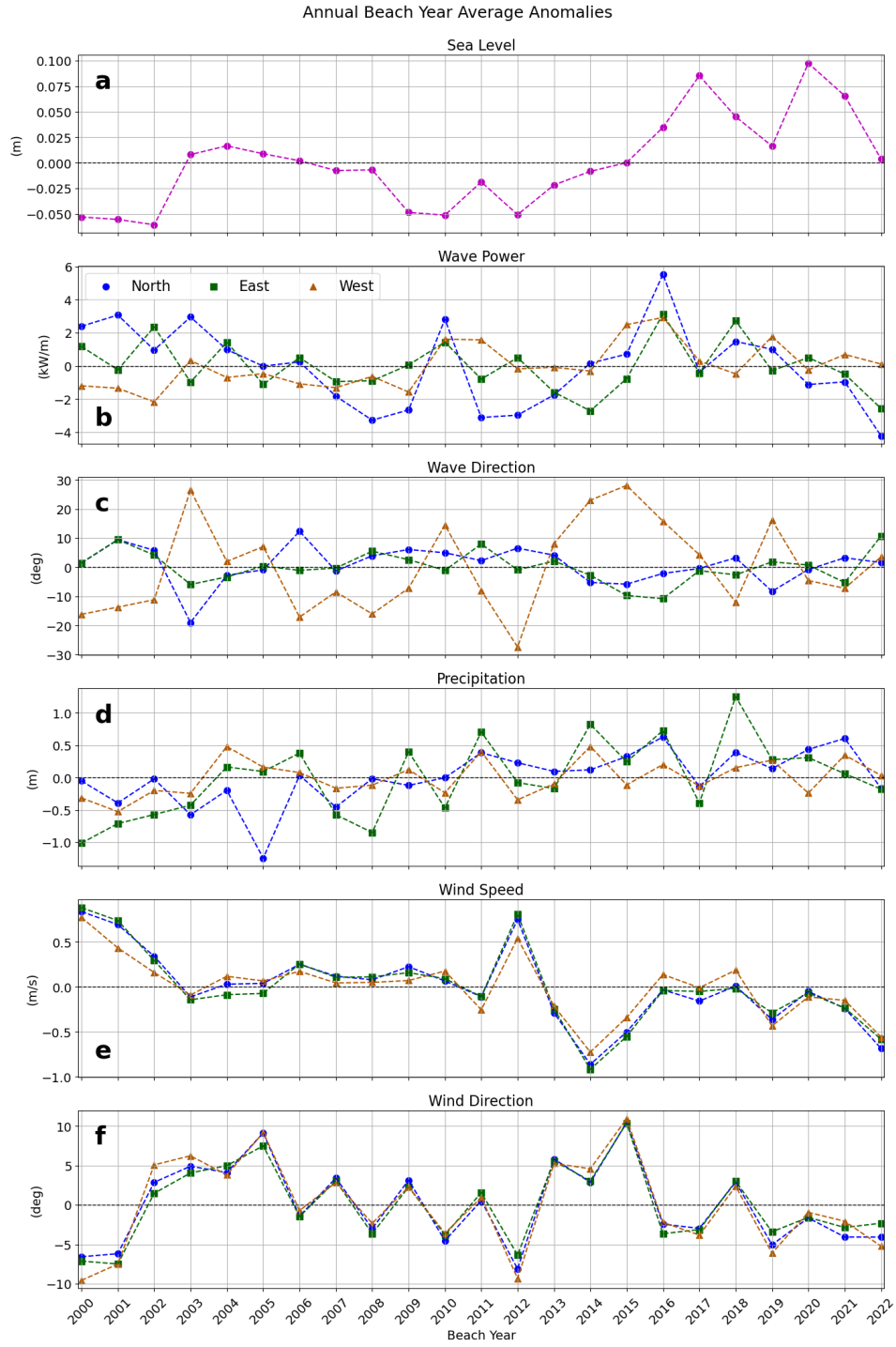


Figure 3.4. Potential beach change drivers: annual beach year average anomalies of (a) sea level, (b) wave power, (c) wave direction, (d) precipitation, (e) wind speed, and (f) wind direction. Blue dashed lines and circles correspond to the north shore, green squares to the east shore, and orange triangles to the west shore.

speed and direction from the ERA5 reanalysis data in the nearest grid cells for each of the three shores.

3.2.4 Linking Annual Beach Width Anomalies to Environmental Drivers

To assess the relationships between interannual beach width changes and potential environmental drivers, we perform a series of statistical analyses at the littoral cell scale. For each cell, we average annual anomalies of beach width alongshore over all transects within the cell, and compare these to the annual anomalies of each potential driver variable described in Section 3.2.3. We compute the Pearson correlation coefficient (r), its p-value to assess significance, as well as the coefficient of determination (r^2) between annual anomalies of beach width and each driver variable (i.e., SLA, wave power, wave direction, precipitation, wind speed, and wind direction). This approach allows us to identify littoral cells where specific environmental drivers show significant correlation with changes in beach width. The coefficients of determination with respect to SLA or wave power (WP) are assigned the same sign as the Pearson correlation coefficient to indicate positive or negative correlations (supplemental table Barnes_Table3.1.xlsx columns B and C).

We perform a multiple linear regression on the annual anomalies of beach width, BW , against anomalies of both sea level, SLA , and wave power, WP , to assess the effect of the combination of these drivers (supplemental table Barnes_Table3.1.xlsx columns E through G):

$$BW = a * SLA + b * WP \quad (3.3)$$

We evaluate the adjusted R^2 to assess whether a model employing this multiple regression is more skillful than the individual forcing terms separately.

We apply Empirical Orthogonal Function (EOF) analysis to extract the dominant spatial and temporal modes of variability in annual beach width anomalies across transects within each cell. Unlike the correlations with spatially-averaged beach widths, EOF analysis

preserves spatial behavior of annual beach width, and can reveal alongshore patterns otherwise obscured. We are primarily interested in the strongest drivers of interannual beach change, so we focus on the first 2 dominant EOF modes explaining the greatest observed variability. We compute the Pearson correlation between the principal component time series for both modes and the annual anomalies of each environmental driver to identify which drivers were most closely associated with the dominant modes of shoreline variability. We report the amount of annual beach width variance explained by each of the EOF modes and coefficients of determination (supplemental table Barnes_Table3.1.xlsx columns I through W). By combining the results of the correlation and EOF analyses, we attempt to identify the environmental drivers most strongly associated with interannual beach width changes in each littoral cell. Cells exhibiting significant and strong driver correlations were flagged for further investigation and discussion in subsequent sections. Confidence interval and p-values are computed assuming that the annual-averaged time series are serially independent. Similar results are obtained assuming that every other year is independent. We consider correlations and coefficients with statistical significance at the 95% confidence level ($p \leq 0.05$).

3.3 Results

3.3.1 Prevalence of Sea Level Anomaly as a Primary Driver

Of the 47 littoral cells analyzed, 32 indicate strong annual island-wide SLA influence beach width behavior. We refer to these 32 cells distributed across the north, east, and west shores of O‘ahu as SLA-driven (yellow, orange, and red cells in Figure 3.5a). These 32 cells can be organized into a hierarchy of SLA influence as follows: all (32) have strongest correlations between their dominant (mode 1) EOF modes and annual SLA compared to the other potential drivers tested (supplemental table Barnes_Table3.1.xlsx column J). This includes cells where alongshore behavior appears to be driven by SLA,

but spatially-averaged beach width anomalies may not strongly correlate with SLA (see 3.3.2). For the 32 SLA-driven cells, the mode 1 EOF explains between 27% and 92% of the observed shoreline variance. For 27 of 32 cells at least 40% variance is explained by mode 1, and for 15 of 32 this exceeds 50%. When the annual average beach width anomalies of these 32 cells are averaged together, the resulting composite time series is strongly negatively correlated with the annual SLA ($r = -0.83$, $r^2 = 0.69$, $p \ll 0.05$; Figure 3.5b). Twelve (12) of those 22 cells exhibit moderate negative correlations ($r < -0.63$, $r^2 > 0.4$) between their alongshore-averaged annual beach width anomalies and the island-wide annual SLA (supplemental table Barnes_Table3.1.xlsx column B). Six (6) of those 12 exhibit the strongest negative correlations ($r < -0.7$, $r^2 > 0.5$).

3.3.2 Spatial Patterns of Shoreline Response to Sea Level Anomaly

Shorelines exhibited two primary modes of response to SLA: alongshore-variable and alongshore-coherent.

Alongshore-Variable Response: Primarily on the northeast shore, the dominant EOF mode reveals significant alongshore variation. Some areas accrete while others erode in response to sea level changes. For example, from Lāʻie Bay to Kokololio (shorelines 23-36), during positive SLA, headlands tended to erode while sand channel entrances accreted, and vice versa during negative anomalies. Here, mode 1 explains 34.2% of the variance and has a strong correlation with SLA ($r^2 = 0.72$; Figure 3.6).

Coherent Alongshore Response: On the north and west shores, the dominant EOF mode shows a more uniform response, with the majority of the shoreline eroding or accreting in unison. For example, along Mokulēʻia (shoreline 1) on the western side of the north shore, mode 1, which explains 51.8% of the variance and has a strong correlation with SLA ($r^2 = 0.59$), describes coherent erosion with positive SLA and accretion with negative SLA (Figure 3.7).

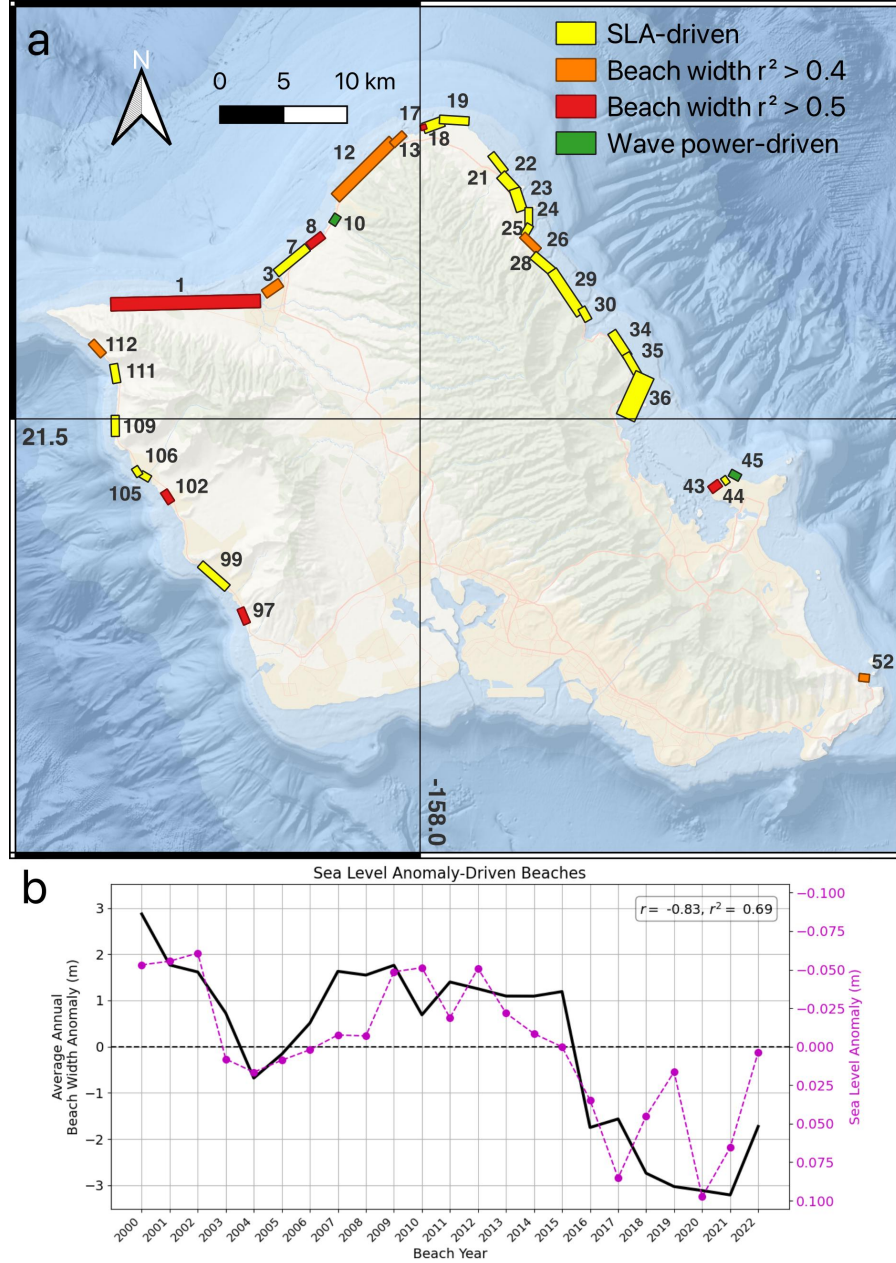


Figure 3.5. Littoral cells that appear to be sea level anomaly (SLA)- or wave power-driven. (a) Cells in yellow, orange, and red (32) are organized into a hierarchy of SLA influence: all have strongest correlations between their dominant (mode 1) EOF modes and annual SLA compared to the other potential drivers tested. Cells in orange and red (12) have moderate negative correlation ($r^2 > 0.4$) between their annual beach width and SLA; cells in red (6) have the strongest negative correlation ($r^2 > 0.5$). Cells in green (2) have moderate negative correlation ($r^2 > 0.4$) between their annual beach width and wave power anomalies and are the only 2 shorelines where wave power correlates best compared to all drivers tested. Basemap from ESRI. (b) The average annual beach width anomalies for all SLA-driven beaches is highly negatively correlated ($r^2 = 0.69$) with annual SLA. Note the inverted right-hand y-axis.

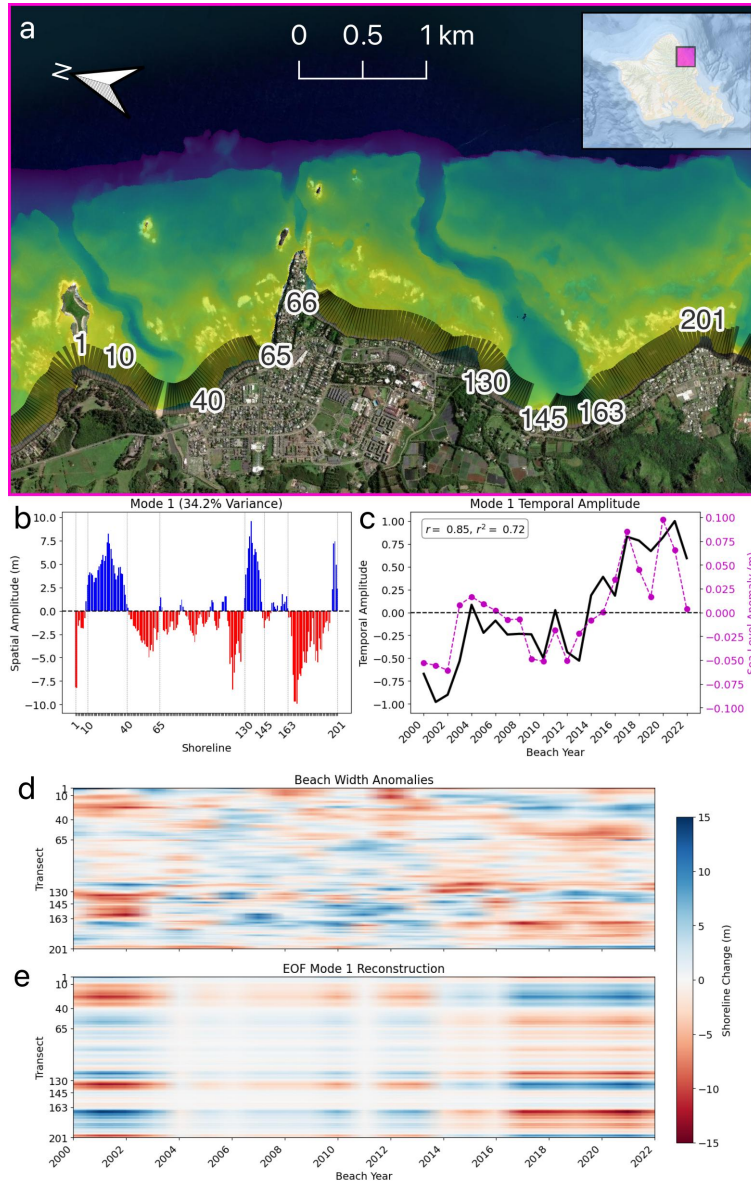


Figure 3.6. Northeast O'ahu from Lā'ie Bay to Kokololio (shorelines 23-26) EOF analysis. (a) Section of coastline composed of 4 littoral cells and a total of 201 transects, as defined by Moskvichev et al. (2025). Transects are labeled at the ends of cells and at boundaries of reef and sand channel structures. Basemap from ESRI; bathymetry from Hawai'i Mapping Research Group, SOEST, UHM. (b) Spatial (blue indicates accretion and red indicates erosion) and (c) temporal (black solid line) amplitudes of the dominant EOF mode of beach width anomaly (accounting for 34% of the observed variance) have a remarkably strong correlation ($r^2 = 0.72$) with annual sea level anomaly (magenta dotted-dashed line). Changes in annual average sea level appear to drive alongshore patterns of erosion and accretion that align with reef and sand channel structure. (d) Observed and (e) mode 1 reconstruction beach width anomalies.

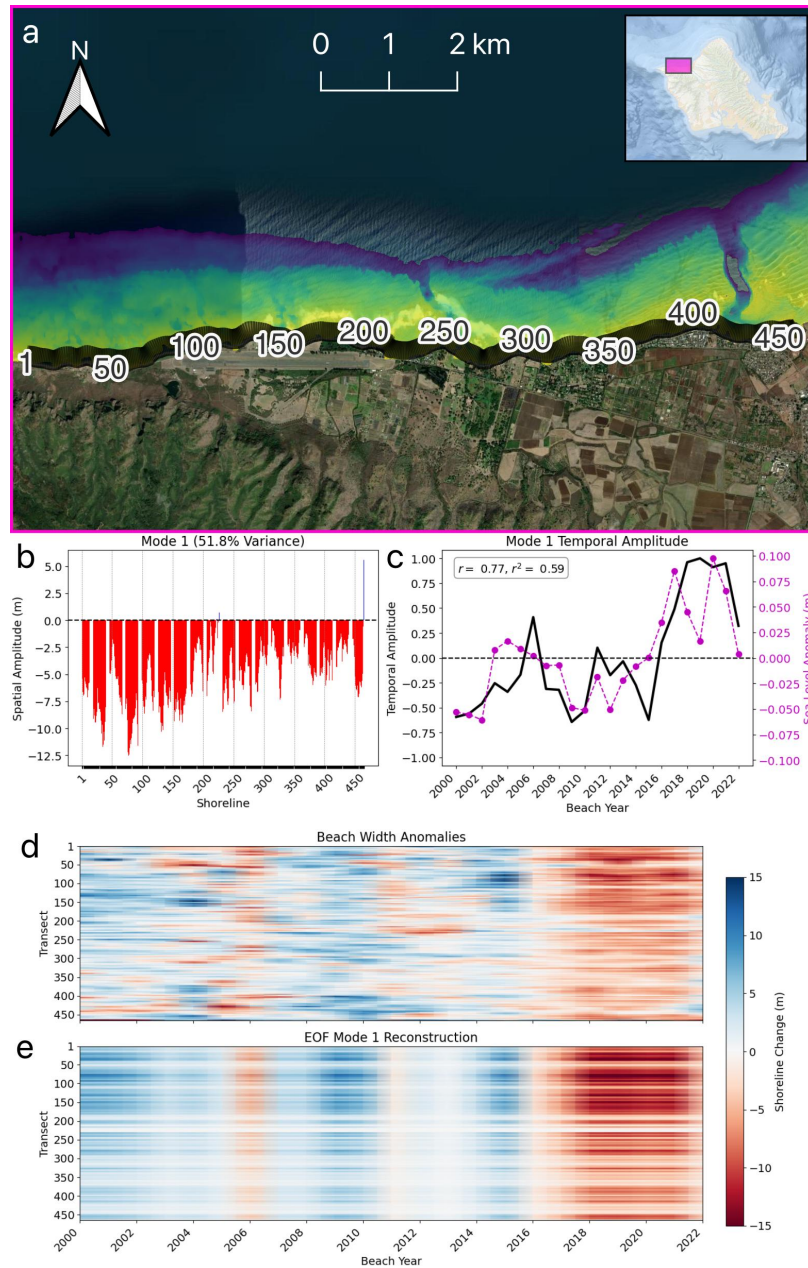


Figure 3.7. Mokulē'ia (shoreline 1) EOF analysis on the north shore of O'ahu. (a) Section of coastline composed of a total of 465 transects, labeled every 50 transects. Basemap from ESRI; bathymetry from Hawai'i Mapping Research Group, SOEST, UHM. (b) Spatial (red indicates erosion) and (c) temporal (black solid line) amplitudes of the dominant EOF mode of beach width anomaly (accounting for 52% of observed variance) have the strongest correlation ($r^2 = 0.59$) with annual sea level anomaly (magenta dotted-dashed line). Changes in annual average sea level appear to drive coherent beach width change. (d) Observed and (e) mode 1 reconstruction beach width anomalies.

3.3.3 Littoral Cells Influenced by Wave Power

Analyses indicate significant influence of wave power on beach width at 12 littoral cells. These 12 cells can be organized into a hierarchy of wave power influence as follows: all 12 exhibit significant correlations between EOF modes 1 or 2 behavior and annual wave power anomalies specific to the site's side of the island, and for 9 of those 12 that correlation is strongest with wave power when compared to the other potential drivers (supplemental table Barnes_Table3.1.xlsx columns K and S). Five (5) of the 12 cells have significant correlations between the EOF mode explaining the greatest beach width variance (mode 1) behavior and annual wave power anomalies. Four (4) of these 5 cells demonstrate significant correlations between annual beach width anomalies and annual wave power anomalies (column C). For 2 of these 4 shorelines (Waimea Bay and Pyramid Rock on the Mōkapu Peninsula), the correlations with wave power ($r^2 = 0.43$) are significantly stronger than the correlations with any other individual driver tested. We refer to these 2 cells as wave power-driven cells (Figure 3.5a).

At both Waimea Bay (shoreline 10) and Pyramid Rock to North Beach on the Mōkapu Peninsula (shorelines 45 and 46, combined for further analysis because they are part of a continuous embayed beach separated only at the shoreline by artificial riprap), wave power correlates best with the primary EOF mode of interannual beach behavior. At Waimea Bay, mode 1 EOF explains 75.39% of the variance. It is weakly correlated with SLA ($r^2 = 0.18$), but more strongly correlated with Waimea Buoy wave power anomalies ($r^2 = 0.42$; Figure 3.8). Interannual beach width variability is highly coherent, with higher wave power anomalies correlated to greater beach erosion (Figure 3.8d). At the Mōkapu Peninsula, mode 1 EOF (46.4% variance explained) is also weakly correlated with SLA ($r^2 = 0.20$), but more strongly correlated with Mōkapu Buoy wave power anomalies ($r^2 = 0.45$; Figure 3.9). Interannual beach width variability is also highly coherent, with higher wave power anomalies correlated with greater beach erosion at most of the shoreline

(Figure 3.9d). Annual beach width anomalies of the Pyramid Rock cell alone (as opposed to mode 1 EOF of the two combined littoral cells) also show significant correlation with wave direction ($r^2 = 0.50$). The multiple linear regression indicates that both wave power and SLA contribute to a relatively skillful (greater adjusted R^2) model for explaining annual beach behavior (columns D through H). These beaches represent relatively unique sites where wave power is the dominant driver, but effects of SLA may still be important.

Three additional beaches illustrate the range of complicated relationships between beach width and the two dominant drivers of beach change. Mā'ili Beach on the west shore (shoreline 100) shows significant correlation between annual beach width and both SLA and wave power, as well as the combination of both drivers through the multiple linear regression. Each of these drivers correlates with the EOF mode 2, but no significant correlation is found for mode 1. For the cell containing Rock Piles beach (shoreline 12), neither the multiple linear regression nor the TWL hindcast, a different metric for the combined effect of wave power and SLA, has a greater correlation with beach width than SLA alone. At Mākaha Beach (shoreline 108), the strongest correlation between beach width and possible drivers is found with SLA ($r^2 = 0.20$), while mode 1 EOF (49.8% variance explained) is correlated strongest with estimates of Wai'anae wave power anomalies ($r^2 = 0.30$). No significant correlation is found with the multiple linear regression.

3.3.4 Analysis of Secondary Environmental Drivers

While no shorelines' annual beach widths correlate strongest with wave direction, windspeed, wind direction, or precipitation, these factors show limited but notable influences on the dominant EOF modes of beach width behavior. Wave direction is significantly correlated with several shorelines' dominant EOF modes (supplemental table Barnes_Table3.1.xlsx columns L and T), including Pyramid Rock (shoreline 45, discussed above) and Hale'iwa Beach (shoreline 3) on the north shore. At Hale'iwa, where the mode 1 EOF (47.3% variance) is strongly correlated with SLA ($r^2 = 0.65$), the mode 2

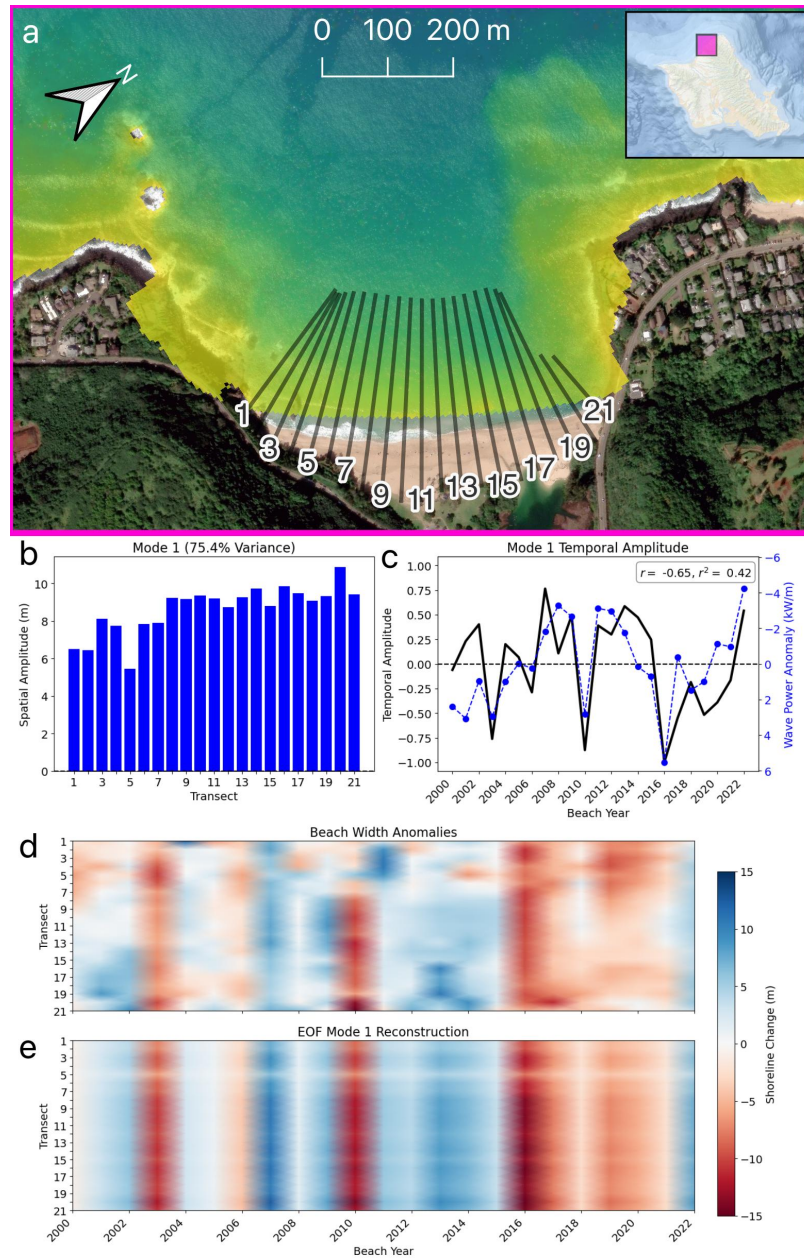


Figure 3.8. Waimea Bay (shoreline 10) EOF analysis on the north shore of O‘ahu. (a) Section of coastline composed of a total of 21 transects. Basemap from ESRI; bathymetry from Hawai‘i Mapping Research Group, SOEST, UHM. (b) Spatial (blue indicates accretion) and (c) temporal (black solid line) amplitudes of the dominant EOF mode of beach width anomaly (accounting for 75% of observed variance) have the strongest correlation ($r^2 = 0.42$) with wave power anomalies (blue dotted-dashed line). Changes in annual average wave power appear to drive coherent beach width change. (d) Observed and (e) mode 1 reconstruction beach width anomalies.

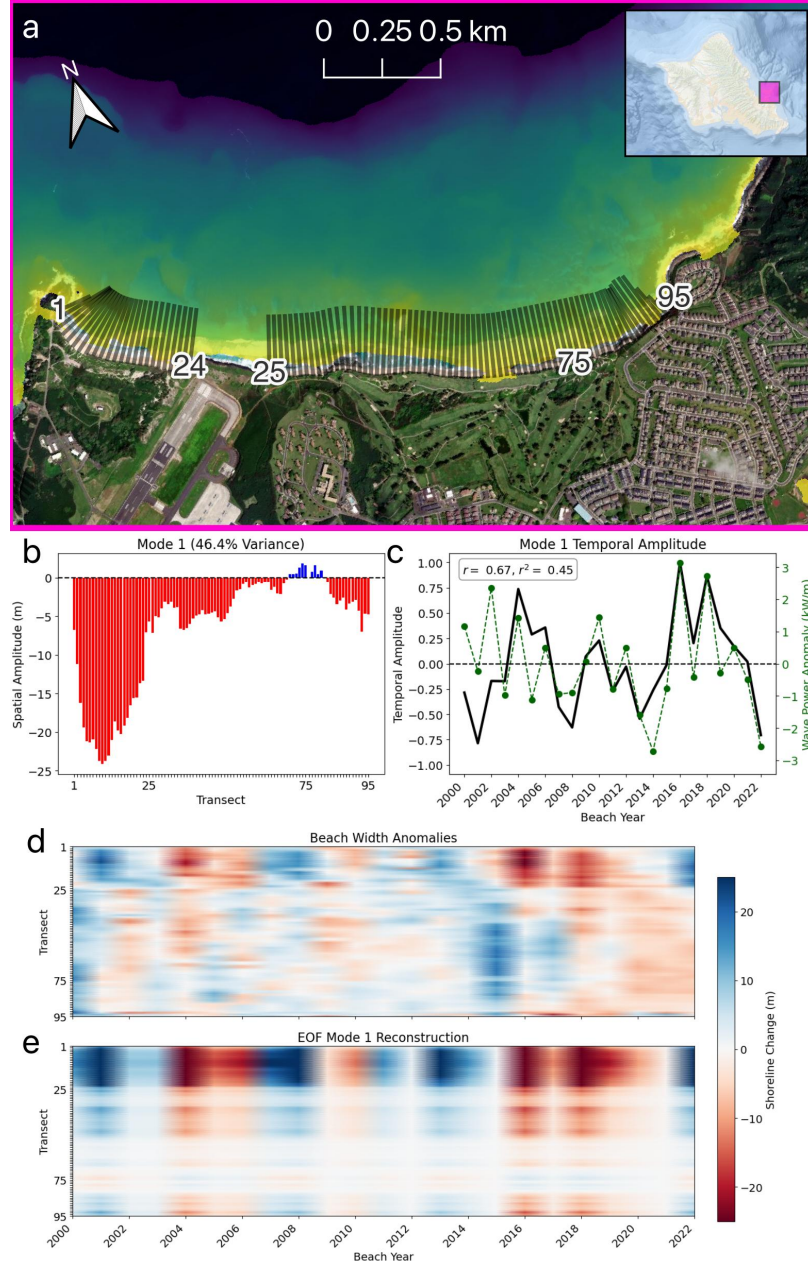


Figure 3.9. Mōkapu peninsula from Pyramid Rock to North Beach (shorelines 45 and 46) EOF analysis on the east shore of O‘ahu at the Kāne‘ohe Marine Corps Base. (a) Section of coastline composed of 2 littoral cells and a total of 95 transects, as defined by Moskvichev et al. (2025). Transects are labeled at the ends of cells and bookending the runway riprap. Basemap from ESRI; bathymetry from Hawai‘i Mapping Research Group, SOEST, UHM. (b) Spatial (blue indicates accretion and red indicates erosion) and (c) temporal (black solid line) amplitudes of the dominant EOF mode of beach width anomaly (accounting for 46% of observed variance) have the strongest correlation ($r^2 = 0.45$) with wave power anomalies (green dotted-dashed line). Changes in annual average wave power appear to drive near-coherent beach width change. (d) Observed and (e) mode 1 reconstruction beach width anomalies.

EOF (16.6% variance explained) has moderate correlation with wave direction ($r^2 = 0.43$). Wind speed and wind direction are significantly correlated with several shorelines' dominant EOF modes (supplemental table Barnes_Table3.1.xlsx columns M, N, U, and V), including from Kailua to Waimānalo (shorelines 49-51) on the windward side of O'ahu. Multiple shorelines' dominant EOF modes have significant correlations with precipitation (supplemental table Barnes_Table3.1.xlsx columns O and W), the strongest of which is from Pua'ena Point to Laniakea Beach (shoreline 7), where EOF Mode 2 (19.5% variance explained) correlates with precipitation anomalies from the Pūpūkea rain gauge ($r^2 = 0.58$; Figure 3.10). Spatial amplitude patterns indicate increased precipitation drives sediment accretion near the 'Anahulu River outflow at the shoreline's western terminus. This secondary mode contrasts with the site's primary variability mode (44.5% variance), which has its strongest correlation with SLA ($r = 0.31$).

3.4 Discussion

The observed patterns of interannual beach width variability across O'ahu's north, east, and west shores (supplemental table Barnes_Table3.1.xlsx) highlight the critical role of SLA in driving shoreline dynamics, particularly in reef-fringed coastal systems. Our analysis reveals that 32 of the 47 littoral cells analyzed (68%) exhibit beach width behavior correlated with annual SLA. Coherent spatial patterns of erosion and accretion often align with reef morphology and sand channel structures. The dominance of SLA-driven shoreline changes in our study (Figure 3.5) suggests that even island-wide interannual sea level variations — such as those linked to ENSO events (Long et al. 2020), atmospheric patterns modulating wind-forcing (Firing et al. 2004), and interannual tidal modulations (Ray and Merrifield 2019) — can significantly modulate sediment transport pathways over reefs, particularly in systems where alongshore circulation dominates over cross-shore processes.

The spatial heterogeneity in beach responses to SLA at some of our study sites

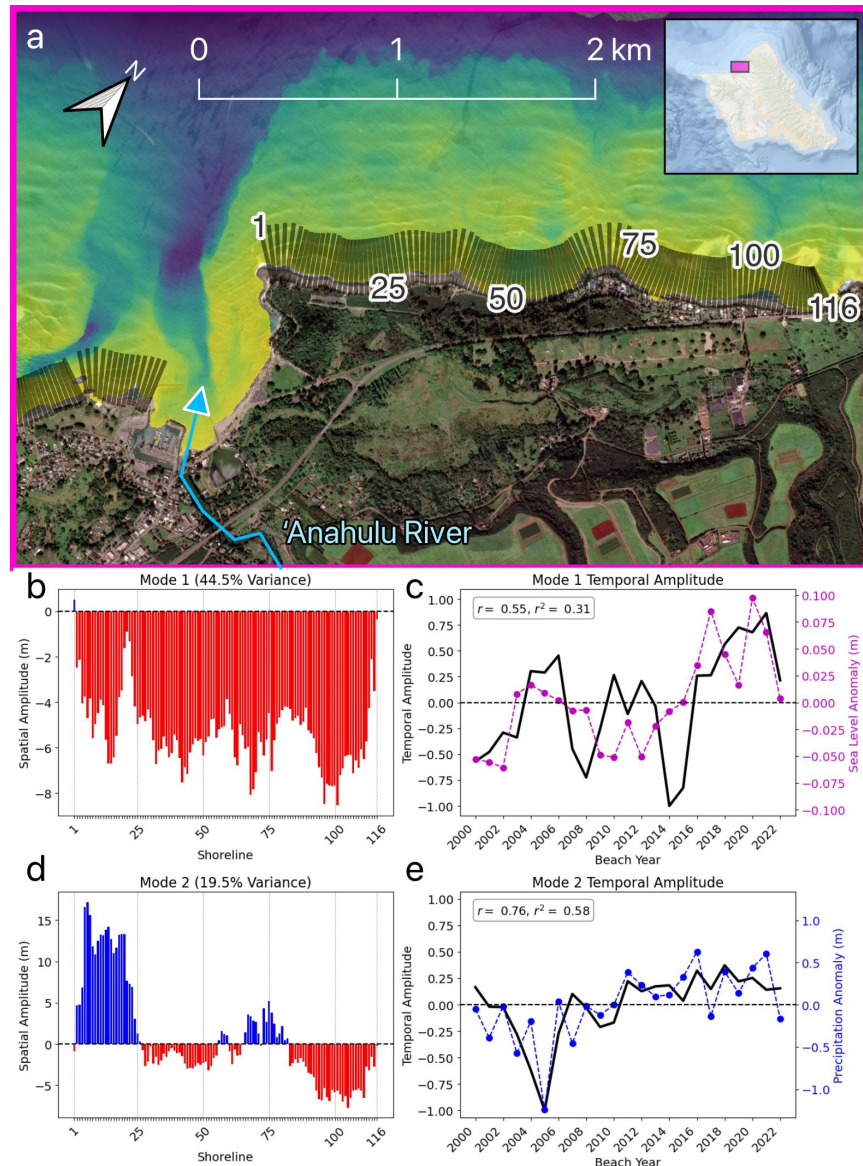


Figure 3.10. Pua'ena Point to Laniakea Beach (shoreline 7) EOF analysis on the north shore of O'ahu. (a) Section of coastline composed of a total of 95 transects, labeled at each end and at 25 transect intervals. Basemap from ESRI; bathymetry from Hawai'i Mapping Research Group, SOEST, UHM. (b) Spatial (blue indicates accretion and red indicates erosion) and (c) temporal (black solid line) amplitudes of the dominant EOF mode of beach width anomaly (accounting for 45% of observed variance) have the strongest correlation ($r^2 = 0.31$) with annual sea level anomaly (magenta dotted-dashed line). (d) Spatial and (e) temporal amplitudes of EOF mode 2 of beach width anomaly (accounting for 20% of observed variance) have the strongest correlation ($r^2 = 0.58$) with the Pūpūkea precipitation anomaly (magenta dotted-dashed line). It appears that precipitation-driven sediment fluxes arising from the 'Anahulu river most significantly affect the Pua'ena point section of this shoreline.

underscores the importance of local geomorphic control. For example, the northeast O‘ahu littoral cells (Figure 3.6) exhibit alternating erosion and accretion patterns that mirror reef platform geometry, consistent with findings from Romine et al. (2016) that these complex reef-protected beaches have responded non-uniformly to modern SLR, dictated by coastal geomorphology (Figure 3.11). This contrasts with the coherent erosion observed at multiple sites, e.g., Mokulē‘ia (Figure 3.7), where broader reef flats and fewer sand channels may promote more uniform sediment redistribution. These results support models emphasizing combinations of cross-shore and alongshore sediment flux modulated by SLA-controlled reef hydrodynamics.

Previous studies of fringing reefs demonstrate that water level controls sea-swell wave energy reaching the shoreline. At three fringing reef sites in the Pacific, Becker et al. (2014) observed that sea-swell wave heights on the reef flats were strongly depth-limited and the dependence varied based on reef geometry. At two of those sites, Merrifield et al. (2014) developed an empirical relationship between water level (tide and breaking-wave setup) and nearshore sea-swell significant wave height. Barnes et al. (2024) observed depth-limited sea-swell wave heights at a fringing reef in American Samoa, and used a one-dimensional, phase-resolving nonhydrostatic wave model to develop a site-specific relationship between nearshore water level, $\bar{h}_A$, and maximum sea-swell significant wave height, $Max(H_{ss}^A)$:

$$Max(H_{ss}^A) = 0.15\bar{h}_A^2 + 0.08\bar{h}_A \quad (m) \quad (3.4)$$

The 0.16 m range (0.04 m standard deviation year to year) in annual SLA during our study period — comparable to 80% (20%) of the 0.2 m projected 2050 SLR for Honolulu based on observation extrapolations (Sweet et al. 2022) — implies that interannual variability of mean sea level already drives beach width fluctuations of similar magnitude to those expected from multi-decadal SLR at sites sensitive to SLA. Relative to SLA from 1905 through 2024, sea level during our study period exhibited a comparable positive trend and

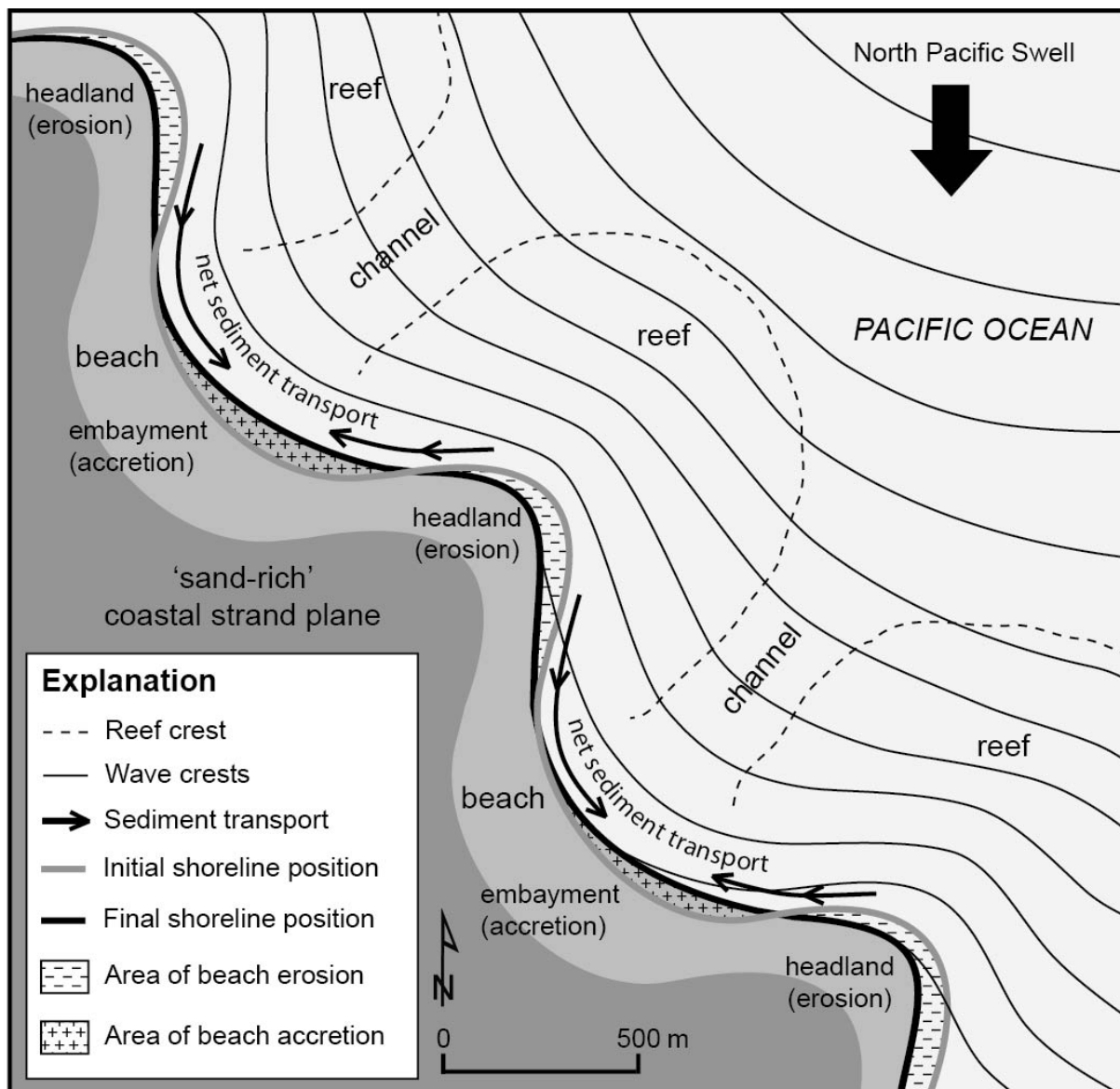


Figure 3.11. A conceptual diagram consistent with observations of historical shoreline erosion patterns from northeast O‘ahu, specifically between Laniloa Beach and Makali‘i Point. The hypothesis is that sea level rise increases erosion at headlands, driving alongshore sediment transport towards embayments fronted by deeper sand channels. Our results suggest the same mechanism is operating on interannual time scales in response to changes in the annual sea level anomaly at multiple O‘ahu shorelines. Reproduced with permission from Romine et al. (2016).

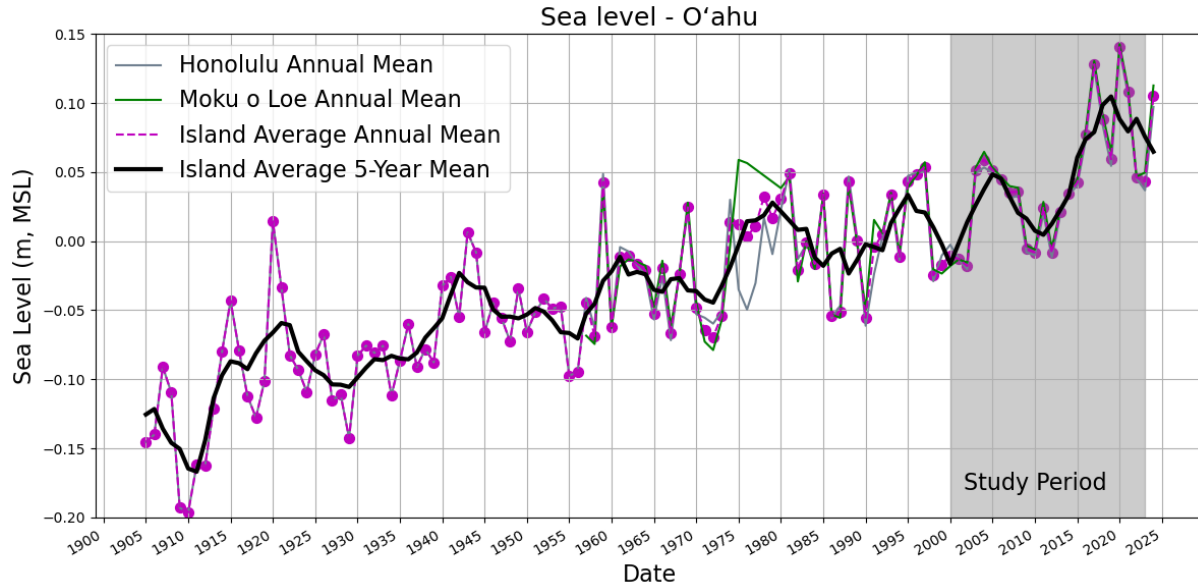


Figure 3.12. Beach year O‘ahu mean sea level from 1905 through 2024, relative to current mean sea level (MSL), from two tide gauges and their island average. The 2000-2022 study period is indicated in grey shading.

interannual variability (Figure 3.12).

Wave conditions emerge as a critical driver for less protected, embayed beaches highly exposed to North Pacific swell, including Waimea Bay (Figure 3.8) and the Mōkapu peninsula (Figure 3.9), where interannual beach width variability correlates strongest with wave power. This aligns with Dail et al. (2000), who documented cross-shore sediment exchange dominating at Waimea, driven by large wave events. Significant correlations with SLA and the multiple linear regression involving both SLA and wave power suggest that it is the combined effect of wave energy and water level that dominates interannual beach variability at these sites. However, the limited number of wave-dominated shorelines suggests that reef morphology buffers most Hawaiian beaches from direct wave forcing — a finding consistent with monitoring studies at Kailua Beach (Norcross et al. 2002) and Waikīkī (Mikkelsen et al. 2022; McDonald et al. 2022). Precipitation-driven sediment fluxes appear negligible at most sites except near major stream outlets like the ‘Anahulu River (Figure 3.10), reinforcing the concerns of Harney and Fletcher (2003) about the

irreplaceability of carbonate sand supplies given accelerating SLR and human shoreline modifications.

These findings have critical implications for coastal management. The 81% of O‘ahu beaches projected to narrow significantly by 2100 (Moskvichev et al. 2025) will likely experience compounding stresses from both chronic SLR and intensified SLA extremes under warming scenarios (Widlansky et al. 2015) not yet directly accounted for in future shoreline modeling. We could see accelerated sediment loss from reef-bound littoral systems, particularly given the 2 orders-of-magnitude difference between SLR and observed historical beach erosion in Hawai‘i (Romine et al. 2013). Adaptive strategies must therefore account for both long-term SLR trajectories and interannual SLA extremes, particularly through preserving natural reef and sediment transport pathways.

A critical limitation of the present study — and of satellite-derived shoreline analyses more broadly — is the scarcity of in situ validation data for O‘ahu’s beaches. While satellite imagery offers unprecedented spatial and temporal coverage, it cannot directly resolve key physical processes such as sediment transport pathways, subaqueous sand storage, or volumetric changes of the beach system. Historical in situ surveys in Hawai‘i have been limited: USGS profile surveys conducted during 4 summers and winters in the 1990s and 2000s (Gibbs et al. 2002) remain among the few available validation datasets for the island except for a small number of beaches. This lack of ground-truthing creates uncertainty regarding the accuracy of satellite-derived shoreline positions, especially in complex settings where instantaneous water lines are affected by tides, sea level anomalies, wave runup, and setup.

To address these limitations, there is a pressing need for expanded and systematic in situ measurement campaigns. Regular subaerial and bathymetric beach profiling, conducted at both seasonal and interannual intervals, would provide essential data to determine where sand is deposited or lost offshore, and how these patterns relate to observed shoreline changes. Such surveys are particularly important for reef-fringed

beaches, where alongshore variability in beach width may not accurately reflect changes in total beach volume due to irregular shoreline morphology. In these settings, average beach width may fail to capture the true volumetric fluctuations of the subaerial beach, as compared to more uniform, alongshore-continuous systems. Without direct measurements, it remains uncertain whether the patterns detected by CoastSat and similar remote sensing frameworks represent real sediment redistribution or are artifacts of variable water levels and shoreline geometry.

Beyond beach profiling, targeted flow measurements over fringing reefs are needed to clarify the mechanisms driving sediment transport. The strong correlation between sea level anomalies and alongshore-coherent beach width changes at many sites suggests that increased water levels may enhance alongshore currents and sediment export through reef channels. However, direct observations of current velocities, sediment fluxes, and channel flushing rates are necessary to determine whether these processes are responsible for the observed shoreline dynamics and to quantify the rates at which sand is lost to deeper water.

3.5 Conclusions

This study leverages 23 years of satellite-derived shoreline data to provide the first island-wide analysis of interannual beach width variability and its environmental drivers across O‘ahu’s north, east, and west shores. SLA is the predominant driver of interannual shoreline change for more than half of O‘ahu’s sandy littoral cells included in our analysis, with coherent patterns of erosion and accretion often aligning with reef and sand channel morphology. Wave power is a significant driver at a minority of sites, particularly at embayed beaches where cross-shore sediment transport dominates during high-energy events. The magnitude of observed interannual beach width fluctuations due to SLA is already comparable to projections for multi-decadal sea level rise, underscoring

the immediate relevance of interannual variability for coastal management and hazard planning. The spatial variability in shoreline response highlights the importance of local geomorphic controls and challenges the applicability of simple shoreline retreat models for Hawai‘i’s complex, reef-fringed coasts.

While satellite-derived analyses continue to advance our understanding of shoreline dynamics and environmental drivers, robust in situ observations remain indispensable for validating remote sensing results and elucidating sediment transport mechanisms. Future research should prioritize systematic field measurements — including beach profiling, bathymetric surveys, and hydrodynamic monitoring — to validate remote sensing results, clarify sediment transport pathways, and aid us in forecasting the evolution of Hawai‘i’s beaches under ongoing sea level rise. Adaptive management of O‘ahu’s beaches must address both chronic sea level rise and the substantial interannual variability driven by SLA and wave climate, with a particular focus on preserving natural sediment transport and reef integrity to enhance shoreline resilience.

ACKNOWLEDGEMENTS

Chapter 3, in full, is currently being prepared for submission for publication of the material. Barnes, Austin T.; Merrifield, Mark A.; O’Reilly, William C.; Mikkelsen, Anna B.; Moskvichev, Richelle U. The dissertation author was the primary investigator and author of this material.

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