

Shoreline Behavior Analysis and Wave-Calibrated Shoreline Modeling

Hindcasting and Projecting Changes at Hasaki Beach

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Shoreline Behavior Analysis and Wave-Calibrated Shoreline Modeling Hindcasting and Projecting Changes at Hasaki Beach



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Acknowledgements

Many writers have reported experiencing intense feelings of depression after completing a major writing project, similar to "postpartum depression." They feel empty, anxious, and even ashamed when reviewing their work. I share these feelings. This dissertation is far from perfect; each time I review it, I find places that increase my anxiety, repeatedly. But when I first presented this work at ICCE and submitted it to an academic journal, the positive feedback encouraged me greatly.

This study primarily originates from my personal interests, and I'm not even sure how much it contributes to the coastal community (though I've crafted a convincing introduction for readers). Initially, upon receiving observation data from Hasaki Beach, like any geomorphologist would do, I categorized it and tried explaining our findings using existing theories. However, the results kicked us badly and taught us that every beach is unique. Thus, I'd prefer to call this dissertation a "personality report of Hasaki Beach," hoping you'll understand it better after reading.

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Abstract

Coastal zones face mounting pressures from climate change and human activities, with sandy beaches worldwide experiencing significant erosion. While equilibrium shoreline models have proven effective for seasonal predictions, they often underestimate extreme events and have limited understanding of their calibration parameters. This limitation becomes particularly concerning as climate change alters wave patterns, highlighting the need to understand how model parameters should adapt to changing wave conditions. This study aims to improve shoreline predictions by connecting calibration parameters with wave climate in a widely used equilibrium model (ShoreFor) and evaluating future shoreline behavior under climate change scenarios, analyzing a unique 33-year dataset of daily to weekly measured beach profiles from Hasaki Beach, Japan, an exposed sandy beach monitored through high-precision plumb line measurements.

Analysis of short-term shoreline behavior revealed asymmetric response patterns, with erosion occurring rapidly during storms while recovery processes were notably slower, and daily variability peaking during August-September transition periods. Long-term analysis using discrete wavelet transform and spectral methods identified distinct annual and semi-annual cycles in shoreline position, strongly correlated with seasonal wave patterns. Using the high-frequency measurements, we employed a segmentation approach to track non-stationary calibration parameters in the ShoreFor model, revealing a significant positive correlation between accretion efficiency coefficient and wave height that was not captured by conventional data assimilation methods. This relationship suggests more efficient shoreline restoration during high-wave periods. Among different forcing variants tested, significant wave height and dimensionless settling velocity demonstrated the most stable performance compared to wave power. This modified model with non-stationary parameters showed superior performance in capturing extreme events and achieved higher correlation with observations compared to the traditional stationary approach during validation. Applying this model to future wave climate projections under RCP8.5 scenario, simulated by the state-of-the-art GCM model, revealed that Hasaki Beach may experience reduced shoreline variability after 2045, with short-term variance (less than 5

years) decreasing to almost half, primarily due to projected decreases in tropical cyclone frequency in the Western North Pacific region.

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Nomenclature

Roman Symbols

H_s Significant wave height

P Wave energy

T_p Peak wave period

U_{10} 10 Meter Wind Speed

Greek Symbols

Ω Dimensionless settling velocity

Acronyms / Abbreviations

CFL Courant-Friedrichs-Lewy

CWT Continuous Wavelet Transform

DWT Discrete Wavelet Transform

EnKF Ensemble Kalman Filter

ENSO El Niño/Southern Oscillation

GCM General Circulation Model

HORS Hasaki Oceanographical Research Station

MHW Mean High Water Level

MLW Mean Low Water Level

MSL Mean Sea Level

ODE Ordinary Differential Equation

PDF Probability Density Function

SIC Sea Ice Concentration

SLR Sea-Level Rise

SST Sea Surface Temperature

Chapter 1

Introduction

1.1 General background of beach erosion

Coastal zones attract significant attention due to their substantial economic and ecological value, as well as their vulnerability to climate change and natural disasters. Coastlines worldwide face mounting pressures from both human activities and environmental changes. Despite the economic opportunities they present, with coastal cities experiencing rapid growth due to their transportation advantages and investment appeal (Merkens et al., 2018), these areas are increasingly threatened by erosion and climate-related hazards. Understanding these challenges requires examining both the current state of coastal erosion globally and the projected impacts of climate change on these vulnerable regions.

Global assessments of coastal change reveal widespread and accelerating erosion patterns across different temporal and spatial scales. Between 1984 and 2015, coastal areas experienced a net loss of land area, with approximately 28,000 km² of permanent land lost—nearly double the amount of land gained during the same period (Mentaschi et al., 2018). This concerning trend is particularly evident in sandy beach environments, where satellite imagery analysis indicates that roughly 24% of the world's sandy beaches are eroding at rates exceeding 0.5 m/year (Luijendijk et al., 2018). The vulnerability of coastal areas is further highlighted by escalating extreme events, with annual coastal overtopping hours—periods when extreme water levels exceed maximum coastal elevations—increasing by nearly 50% over the past two decades (Almar et al., 2021).

However, regional analyses reveal more complex and heterogeneous patterns of coastal change. In Australia, a comprehensive study of coastline changes between 1988 and 2019 found that while 22% of non-rocky coastline underwent significant modification, the continental-scale erosion (11.1%) and accretion (11%) rates showed remarkable balance. This apparent equilibrium masks substantial regional variations, with western coasts

dominated by recession while southern and eastern coastlines exhibited predominant growth patterns. In extreme cases, some locations experienced dramatic changes of up to 14.5 m per year (Bishop-Taylor et al., 2021).

The Japanese coastline presents a distinct temporal evolution of erosion patterns, illustrating the combined effects of natural processes, human intervention, and conservation efforts. While coastal erosion remained relatively stable from 1900 to 1950, the period between 1950 and 1990 saw significant shoreline retreat ranging from 20 to 200 m, primarily attributed to coastal development and dam construction. This trend was eventually stabilized post-1990 through the implementation of active beach conservation measures (Yoshida et al., 2013). The Japanese experience demonstrates both the substantial impact of human activities on coastal systems and the potential effectiveness of targeted conservation strategies.

1.2 Morphodynamic mechanism

Having examined the patterns of shoreline change across different coastal regions, it is essential to understand the underlying mechanisms driving these morphological changes. Beach morphodynamics refers to the mutual interactions between beach morphology and hydrodynamic processes (including waves, tides and wave-driven currents) that drive sediment transport and bed changes (Figure 1.1(a); Castelle and Masselink, 2023). These morphodynamic processes exhibit both cross-shore and alongshore components, operating across multiple timescales from individual waves to seasonal and interannual variations.

Cross-shore sediment transport on sandy beaches is fundamentally controlled by the balance between onshore and offshore-directed transport mechanisms. At any point along a beach profile, the net sediment transport results from the competition between onshore-directed transport driven by wave nonlinearities (skewed and asymmetric near-bed orbital velocities) and offshore-directed transport driven by undertow currents, with infragravity waves also playing a role in advecting suspended sediment (Osborne and Greenwood, 1992; Ruessink et al., 1998; Smith and Mocke, 2002). During storms, intense wave breaking generates strong undertow currents that transport sediment seaward, resulting in offshore sandbar migration and beach erosion. Conversely, during low to moderate energy conditions, the near-bed wave-nonlinearity-driven bedload transport results in slow onshore sandbar migration concurrent with beach and berm accretion.

In contrast to cross-shore processes, alongshore sediment transport on open sandy beaches occurs in an environment with no initial process gradients, as offshore wave

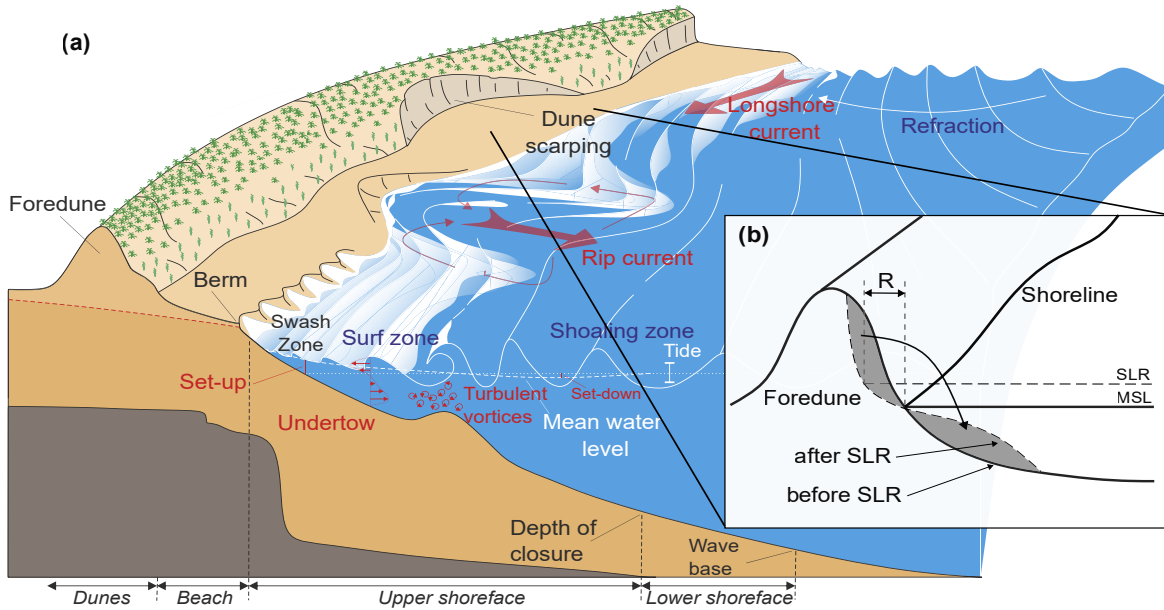


Fig. 1.1 (a) Schematics of the primary hydrodynamic and sediment transport processes occurring on wave-dominated beaches (Adapted from Castello and Masselink (2023)); (b) Beach retreat (R) and erosion with SLR;

conditions are typically uniform alongshore. However, the nearshore region often develops a range of rhythmic features through different feedback mechanisms between flow and morphology. These patterns include beach cusps (tens of meters), megacusps (hundreds of meters), and three-dimensional surf zone bars (tens to thousands of meters) (Coco et al., 1999; Short, 1999; Thornton et al., 2007). While these features were initially thought to be created by edge waves (Holman and Bowen, 1982), more recent research suggests they develop through self-organization processes, where interactions between fluid flow, sediment transport and evolving morphology create positive feedback mechanisms (Coco and Murray, 2007). These feedback processes are particularly evident during accretionary conditions, when general onshore sediment transport dominates.

The sea-level rise (SLR), either temporarily through storm surge or permanently due to climate change, can significantly enhance beach berm erosion. The joint effect of elevated water levels and wave action erodes the berm, with the eroded sediment typically depositing at the upper shoreface as shown in Figure 1.1 (b). This process follows the concept known as the Bruun Rule (Bruun, 1962), which suggests that beaches respond to SLR through an upward and landward translation of the beach profile, maintaining an equilibrium shape relative to the new water level.

By wave set-up and swash, waves contribute to water level changes across different time scales, from single extreme events to multidecadal changes. This multi-scale

influence of waves has significant implications for future water level projections, as wave-driven contributions could either amplify or dampen the effects of sea-level rise along coastlines (Melet et al., 2018). At a global scale from 1979 to 2012, shoreline erosion across the Pacific basin is strongly modulated by El Niño/Southern Oscillation (ENSO), where El Niño events intensify erosion in the northeast Pacific while La Niña events amplify erosion in Australia and the Pacific Northwest, primarily through ENSO's influence on wave energy flux, wave direction, and water levels (Barnard et al., 2015). A more comprehensive analysis using 38 years of satellite imagery across 8,300 km of Pacific coastline further revealed that approximately one-third of all monitored beaches experience significant erosion during El Niño phases, with the Eastern Pacific being particularly vulnerable to widespread erosion, especially during major events like the 1997/1998 El Niño. Conversely, La Niña phases are associated with significant accretion for about one-quarter of Pacific beaches, although regions like southeast Australia experience substantial erosion during these periods (Vos et al., 2023). These observed patterns suggest that future changes in ENSO amplitude and frequency could have significant implications for coastal erosion and accretion patterns across the Pacific basin.

1.3 Climate change impact

Climate change is amplifying coastal vulnerabilities through multiple mechanisms. The 6th Assessment Report of IPCC (2023) projects significant SLR by 2100, with estimates ranging from 0.28 to 0.55 m under the most optimistic scenario (SSP1-1.9) to 0.63 to 1.01 m under the high-emission scenario (SSP5-8.5). The climate change-driven SLR combined with coastal erosion could cause the near extinction of almost half of the world's sandy beaches by 2100, with 35.7-49.5% of sandy beaches projected to retreat by more than 100 m under RCP8.5 scenario, though moderate greenhouse gas emission mitigation could prevent 40% of the projected shoreline retreat (Vousdoukas et al., 2020). More than this, the SLR could lead to catastrophic coastal flooding, with projections showing that without adaptation, 0.2-4.6% of global population would face annual flooding by 2100, potentially causing losses of up to 9.3% of global GDP under the most severe scenarios (Hinkel et al., 2014).

Beyond rising SLR, coastal areas face evolving wave and storm patterns. Climate change is projected to significantly alter global wave patterns through its effects on tropical cyclones and atmospheric circulation. At the global scale, wave heights are projected to exhibit distinct spatial patterns, increasing in the Southern Ocean and decreasing in the subtropics, with future changes in annual mean wave height within about ± 0.3 m (Shimura

et al., 2015). The changes in wave climate reflect a delicate balance between decreasing storm frequency and increasing storm intensity under warmer conditions. These changes in wave climate and storm patterns can potentially accelerate erosion processes and increase the risk of coastal flooding or have opposite impact. The compound effects of these changes are significant. Climate change will dramatically accelerate coastal overtopping, with globally aggregated annual overtopping hours projected to increase up to 50 times by 2100 under RCP8.5 scenario. This acceleration will be faster than sea-level rise itself due to the combined effects of sea-level rise, storm surge, and wave interactions (Almar et al., 2021).

Regional impacts show considerable variation. Along the US Southeast Atlantic coast, climate change and sea level rise are projected to expose over 70% of coastal residents to shallow groundwater hazards, potentially destroy up to 80% of present-day beaches, and significantly amplify storm-driven flooding impacts that could affect approximately 50% of coastal residents by 2100, with these impacts further exacerbated by land subsidence affecting over 1 million residents (Barnard et al., 2024). In the Western North Pacific region, the patterns are different. During winter, wave heights show robust decreasing trends driven by changes in the West Pacific atmospheric pattern (Shimura et al., 2016). More recent projections indicate wave heights and storm surges in this region will decrease (approximately -200 cm/century for annual maximum significant wave height and -20 cm/century for storm surge) due to reduced tropical cyclone frequency, despite individual storms potentially becoming more intense (Shimura et al., 2022). Similarly, mega-ensemble projections across the Western North Pacific and East Asia coastal regions reveal more complex patterns, while the annual frequency of extreme events may decline, the magnitude of severe storms could increase, leading to more impactful storm surges and wave conditions, particularly around coastal megacities like Tokyo and Osaka where surge heights are projected to increase by 0.3-0.45 m for 100-year return period events (Mori et al., 2019).

While these studies provide valuable insights into future wave climate and storm surge patterns, how these changes will specifically impact coastal morphology and shoreline evolution remains less understood. The complex interactions between changing wave patterns, storm frequency and intensity, and coastal processes need further investigation to better predict future shoreline changes. This is particularly important as changes in wave climate could either accelerate or potentially reduce coastal erosion depending on local conditions and wave characteristics. Therefore, this thesis focuses on investigating how shoreline interact with wave conditions and how projected changes in wave climate

under future scenarios will influence shoreline evolution, aiming to better understand and quantify the morphological response of coastal systems to climate change.

1.4 Beach monitoring

To understand and predict these morphodynamic changes and assess climate change impacts on coastlines, long-term, high-quality monitoring of beach morphology is essential. Different approaches to beach monitoring have emerged over time, each with their own advantages and limitations for capturing various temporal and spatial scales of coastal change.

Video-based monitoring techniques have been employed since the late 2000s as a localized automated remote sensing approach, providing high-resolution and high-frequency shoreline observations (Davidson et al., 2007; Holman and Stanley, 2007; Valentini et al., 2017). More recently, aerial photography and satellite imagery have emerged as tools for monitoring shoreline changes, offering extensive area coverage and historical data suitable for large-scale comparisons (Luijendijk et al., 2018; Vos et al., 2019; Almar et al., 2023). However, these methods face several limitations: cloud coverage affects sampling frequency, and the accuracy is influenced by wave run-up conditions that impact instantaneous water levels (Castelle et al., 2021). In macrotidal environments, additional challenges arise as low tide images often need to be discarded due to the presence of complex bars and rip channels, while temporally varying beach slopes further complicate measurements (Castelle et al., 2021; Konstantinou et al., 2023; Warrick et al., 2024).

For improved accuracy in local studies, GPS survey techniques (Morton et al., 1993; Harley et al., 2011) and LiDAR technology (Blenkinsopp et al., 2010; Brodie et al., 2015) are utilized to monitor beach profiles. These methods provide high precision but are typically resource-intensive and limited in spatial coverage. Traditional surveying techniques using the plumb line method, although time-consuming and labor-intensive, provide exceptional accuracy with measurement uncertainty of approximately ± 5 cm in elevation (translating to ± 1 m in shoreline position) and are independent of water levels (Banno et al., 2020). However, this method relies on the availability of a fixed structure, such as a pier, which can only be constructed in certain locations within the surf zone.

For comprehensive understanding of beach morphodynamics and reliable model development, three key monitoring requirements emerge: consistent long-term measurements spanning multiple years to decades, high temporal resolution capable of capturing both storm events and seasonal changes, and high measurement accuracy independent of environmental conditions. Such datasets are exceptionally rare, particularly in regions

expected to experience significant climate change impacts. This study utilizes one such dataset from **Hasaki Beach**, Japan, where unique monitoring infrastructure has enabled continuous, high-precision measurements spanning over three decades. The dataset combines daily beach profile measurements with measurement uncertainty of ± 1 m in shoreline position, notably superior to satellite imagery (± 5 m uncertainty) and camera-based measurements (± 2 m uncertainty). This exceptional precision, combined with consistent long-term daily sampling, provides an unprecedented opportunity to analyze beach response across multiple temporal scales, from individual storms to decadal trends.

Future developments in monitoring technology are expected to reduce costs while improving accuracy and resolution, potentially enabling better documentation of previously unmeasured beach processes and enhancing our ability to predict and manage coastal change (Banno, 2023).

The background presented in this chapter has highlighted several critical challenges in coastal management: accelerating global coastal erosion, complex morphodynamic responses to changing wave conditions, and uncertainties in predicting future shoreline evolution under climate change scenarios. While recent advances in monitoring technologies have improved our understanding of coastal processes through datasets like that from Hasaki Beach, translating this understanding into reliable predictions remains a fundamental challenge. Particularly challenging is the need to capture shoreline responses across multiple temporal scales, from rapid storm impacts to long-term climate change effects, while maintaining computational efficiency and practical applicability. These challenges necessitate careful consideration of different modeling approaches, which will be examined in Chapter 2.

Chapter 2

Review of numerical modeling of beach morphology

The complex morphodynamic processes described in Chapter 1 present significant challenges for numerical modeling. A fundamental tension exists between the desire to capture detailed physical processes and the need for computationally efficient predictions over longer time scales. Models must balance several competing requirements: they must be sophisticated enough to capture key physical processes, yet simple enough to remain computationally feasible for long-term predictions; they need to incorporate both cross-shore and longshore processes while remaining practical for coastal management applications.

This chapter examines the evolution of beach morphology models, from early empirical approaches to contemporary reduced-complexity models, analyzing their relative advantages and limitations. Through this review, we identify current research gaps and establish the foundation for developing improved modeling strategies for predicting shoreline evolution under changing wave climates.

2.1 Numerical models

Sandy beaches are highly dynamic systems whose evolution reflects the complex interactions of environmental forcing, such as waves, tides, and currents, with varying sediment conditions across different spatial and temporal scales (Castelle and Masselink, 2023). To understand the drivers behind shoreline evolution and reproduce the process, numerical models have been developed to simulate the shoreline change. Ranasinghe (2020) summarized the existing models by time scales and spatial-aggregation levels into three

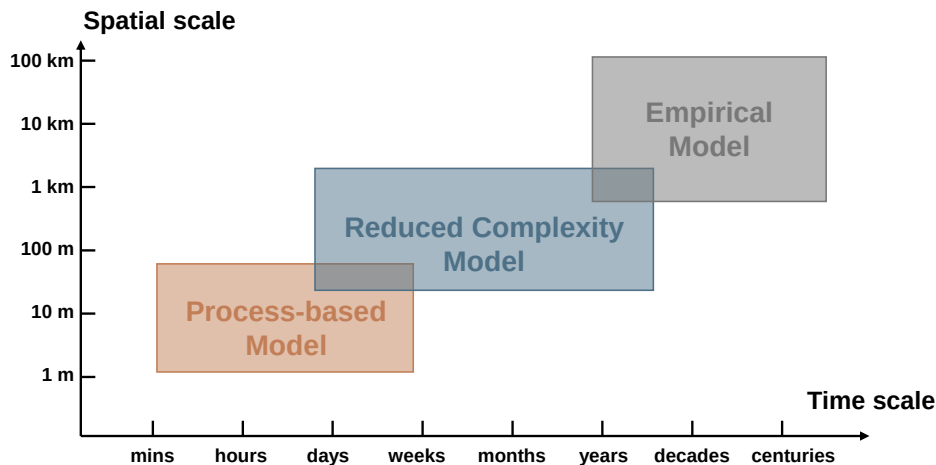


Fig. 2.1 Time-space scale diagram of three types of model.

categories as Figure 2.1 shows: **process-based models**, **empirical models**, and **reduced complexity models**.

Process-based models, like MIKE21, XBeach, and Delft3D, aim to resolve the physics involved in hydrodynamics and sediment transport (Warren and Bach, 1992; Roelvink et al., 2009; Lesser, 2009). These models typically employ a quasi-3D approach (vertically uniform), incorporating both cross-shore and longshore hydrodynamics to simulate coastal processes across episodic, medium-term, and long-term temporal scales. The study area is generally schematized into computational grids to capture the spatial variability of morphodynamic processes. Process-based models have demonstrated particular success in simulating dune erosion during extreme storms, wave run-up and overtopping, post-storm beach recovery, nearshore bar migration, sand nourishment evolution, morphological response to coastal structures, and beach overwash processes (e.g., Grunnet et al., 2004; Ruessink et al., 2007; Roelvink et al., 2009; McCall et al., 2010; Luijendijk et al., 2017; Karunarathna et al., 2018; Roelvink et al., 2018). Their ability to resolve detailed hydrodynamics and sediment transport processes makes them valuable tools for coastal engineering design and impact assessment of short-term interventions.

While process-based models can simulate cross-shore sediment transport and beach profile deformation in detail, they face significant challenges, particularly for long-term simulations. The computational demands are intensive due to several factors. First, the need for fine spatial resolution to accurately capture morphodynamic processes results in a large number of grid cells. Second, the Courant-Friedrichs-Lewy (CFL) criterion imposes strict limitations on the time step size to maintain numerical stability, especially with fine spatial discretization. This combination of fine spatial resolution and small time steps leads to prohibitively long computation times. Furthermore, process-based

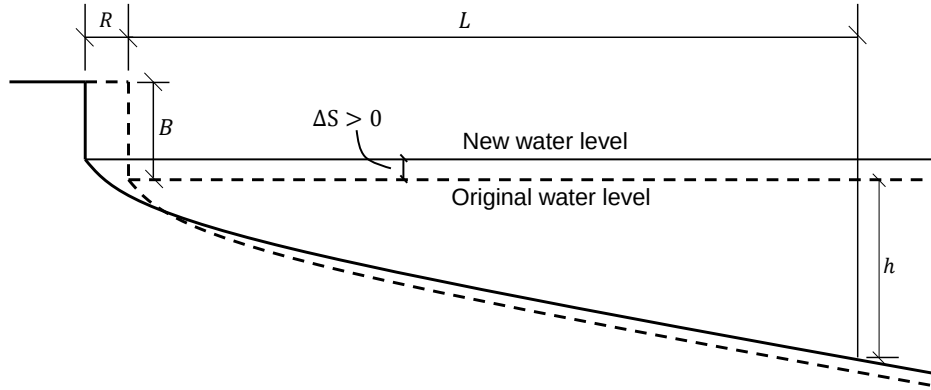


Fig. 2.2 Diagram for profile response due to sea level rise according to Bruun Rule.

models often exhibit numerical instability in long-term simulations. Small perturbations or numerical fluctuations can amplify over time, potentially leading to significant errors in the predicted morphological evolution. This inherent instability becomes particularly problematic when simulating decadal-scale coastal changes.

Recent advances in parallel computing techniques have helped address some of these computational limitations. For instance, Luijendijk et al. (2019) demonstrated that parallel processing can significantly reduce simulation times. However, even with these improvements, a 30-year long-term simulation still requires days to weeks of computation time. Moreover, these computational optimizations do not address the fundamental challenges of numerical stability in long-term predictions.

Opposite to process-based models, empirical models highly aggregate the coastal area evolution in space and in time. Bruun (1954) firstly noted that the shape of the nearshore beach profile along the coast of Denmark followed a simple power law with distance seaward from the shoreline. The power law is later examined by Dean (1977) fitting with field data from Atlantic Ocean and Gulf of Mexico beaches and Wang and Kraus (2005) using large-scale laboratory experiment in the following form:

$$h = Ax^{2/3} \quad (2.1)$$

Where h is the still water depth, x is the horizontal distance from shoreline ($h = 0$), and the constant of proportionality A is related to the size of the beach sediment (Dean, 1977; Moore, 1982). Following such a framework of equilibrium profile, some empirical models for cross-shore profile changes consider the equilibrium profiles as target profiles and estimate the shoreline change based on the distance between current beach profile and equilibrium profile with given hydrodynamic conditions.

The first empirical model of beach profile change, Bruun Rule, was introduced by Bruun (1962) (Figure 2.2), giving a linear relationship between sea level rise and shoreline recession based on equilibrium profile theory as follow:

$$R = \frac{\Delta SL}{h + B} \quad (2.2)$$

Where R is the shoreline recession, S is sea level rise, h is the depth of closure, B is the dune height above sea level, and L is the horizontal length from dune peak to depth of closure. The model assumes that as sea level rises, the beach profile maintains its equilibrium shape but shifts landward and upward, with eroded upper beach material being deposited offshore to maintain a constant water depth. Following Bruun Rule, Dean (1991) extended the beach profile response theory by incorporating wave effects (wave setup, wave height changes), demonstrating that storm surge and wave run-up significantly influence the equilibrium profile during storms. Based on observations, the response of a beach to steady-state forcing conditions follows an approximately exponential relationship over time:

$$R(t) = R_{\infty}(1 - e^{-t/T_s}) \quad (2.3)$$

where $R(t)$ represents the beach profile response (recession or advancement) at time t , R_{∞} is the maximum potential response at equilibrium, and T_s is the characteristic time scale controlling how quickly the system approaches equilibrium.

This exponential relationship suggests that the rate of profile change must be proportional to the difference between the current profile state and its equilibrium state. Based on this observation, Kriebel and Dean (1993) proposed an ordinary differential equation (ODE):

$$\frac{dR(t)}{dt} = \frac{1}{T_s}[R_{\infty} - R(t)] \quad (2.4)$$

where $dR(t)/dt$ represents the instantaneous rate of shoreline change.

In reality, the equilibrium profile depends on time-varying hydrodynamic conditions such as water level and wave conditions. Therefore, we can express the maximum beach response as R_{∞} multiplied by a time-dependent forcing function $f(t)$, modifying Eq. (2.4) to:

$$\frac{dR(t)}{dt} = \frac{1}{T_s}[R_{\infty}f(t) - R(t)] \quad (2.5)$$

Solving this first-order linear differential equation yields:

$$R(t) = \frac{R_{\infty}}{T_s} \int_0^t f(\tau) e^{-(t-\tau)/T_s} d\tau \quad (2.6)$$

where τ is the integration variable representing past time points between 0 and t . The exponential term $e^{-(t-\tau)/T_s}$ acts as a weighting function that gives more importance to recent forcing conditions (when τ is close to t) and less importance to conditions from the distant past (when τ is much smaller than t).

Substituting Eq. (2.6) back into Eq. (2.5) yields the convolution form:

$$\frac{dR(t)}{dt} = \frac{R_\infty}{T_s} \left[f(t) - \frac{1}{T_s} \int_0^t f(\tau) e^{-(t-\tau)/T_s} d\tau \right] \quad (2.7)$$

This convolution integral represents how the beach profile's response at any time t depends on the complete history of forcing conditions, with an exponentially decreasing memory of past events. This formulation captures the beach's "memory" of previous conditions while giving greater weight to more recent forcing events, providing a more realistic representation of beach profile evolution compared to instantaneous equilibrium assumptions.

This approach marks a significant advancement in shoreline modeling methodology. By incorporating simplified descriptions of fundamental system physics through the proposed ODE, it enables tracking of dynamic beach profiles while delivering estimates of system response to forcing without the computational intensity of full process-based simulations. This methodology establishes the framework for what is now known as reduced complexity modeling, bridging the gap between purely empirical and full process-based approaches. Subsequent shoreline models have largely built upon this concept.

Miller and Dean (2004) employed a semi-implicit scheme to solve this ODE, enabling it to capture complex shoreline variations numerically rather than analytically through time steps. This approach has become foundational in reduced complexity models. They further simplified Eq. (2.5) to:

$$\frac{dy(t)}{dt} = k(y_{eq}(t) - y(t)) \quad (2.8)$$

where k is a constant governing the rate at which the shoreline position y approaches equilibrium y_{eq} . They explored various parameterizations for the rate constant k governing shoreline response as following forms:

$$k \propto \begin{cases} \text{constant} \\ \Omega(t) = H_s / w T_p \\ H_s(t)^2 \\ H_s(t)^3 \end{cases} \quad (2.9)$$

where Ω is the dimensionless settling velocity. While the rate constant k can differ between erosion and accretion phases, none of the proposed forms emerged as definitively superior when applied to beaches across the United States.

Building on Miller and Dean (2004), Yates et al. (2009) proposed a generalized equilibrium model (hereafter, Y09) that incorporated different rate constants for erosion and accretion based on shoreline position:

$$\frac{dS}{dt} = C^\pm E^{1/2} [E - E_{eq}(S)] \quad (2.10)$$

$$E_{eq}(S) = aS + b \quad (2.11)$$

where the equilibrium energy E_{eq} is defined as a linear function of shoreline position S , with $C^\pm$, a , and b serving as calibration parameters. Y09 extended Eq. (2.8) by introducing the factor $E^{1/2}$ to prevent unrealistic shoreline changes during low wave energy conditions. Fundamentally, Eq. (2.10) shares the same structure as Eq. (2.8) and Eq. (2.5), with shoreline position explicitly included in the ODE right-hand side acting as a damping term.

Drawing from both Wright et al. (1985) and Y09, Davidson et al. (2013) developed the ShoreFor model, which defines equilibrium based on past wave conditions:

$$\frac{dS}{dt} = C^\pm P^{1/2} [\Omega_{eq}(t) - \Omega(t)] + b \quad (2.12)$$

$$\Omega_{eq} = \left[\sum_{i=1}^{2\phi} 10^{-i/\phi} \right]^{-1} \sum_{i=1}^{2\phi} \Omega_i 10^{-i/\phi} \quad (2.13)$$

Like Y09, the ShoreFor model maintains $k \propto H$. Following Wright et al. (1985), it defines the equilibrium state using past wave conditions convolved with an exponentially decaying weight, similar to Eq. (2.7). However, unlike the models of Miller and Dean (2004) and Y09, the ShoreFor model's governing equation (Eq. (2.12)) does not explicitly include shoreline position.

While these models require calibration of free parameters whose physical interpretation remains challenging, they have demonstrated practical success. Y09 successfully captured both seasonal cycles and multiyear erosional trends across 12 transects at Ocean Beach, California (Yates et al., 2011). Similarly, Splinter et al. (2014) applied the ShoreFor model to twelve global shoreline datasets, and despite treating calibration parameters as site-specific and stationary, successfully reproduced dominant seasonal cycles at exposed beaches.

Table 2.1 Reduced complexity shoreline model comparison

Model name	Governing equation	Cross-shore	Alongshore	Sea-level rise
CoSMoS (Vitousek et al., 2017)	$\frac{\partial Y}{\partial t} = -\frac{1\partial Q}{d\partial X} + CE^{1/2}\Delta E$ $-\frac{c}{\tan\beta}\frac{\partial S}{\partial t} + v_{lt}$	Yates et al. (2009)	CERC (USACE, 1984)	Bruun (1962)
LX-Shore (Robinet et al., 2018)	$F(t + \Delta t) = F(t) + \Delta F_I(t) + \Delta F_c(t)$	Davidson et al. (2013)	CERC (USACE, 1984)	[-]
COCOONED (Antolínez et al., 2019)	$\frac{\partial Y_S}{\partial t} = \frac{-1}{d}\frac{\partial Q_L}{\partial x} + K_c(Y_{S,eq} - Y_S)$ $+ \frac{-1}{d}(q_x + q_y)$	Miller and Dean (2004)	CERC (USACE, 1984)	[-]
ShorelineS (Roelvink et al., 2020)	$\frac{\partial n}{\partial t} = -\frac{1}{D_c}\frac{\partial Q_s}{\partial s} - \frac{RSLR}{\tan\beta}$ $+ \frac{1}{D_c}\sum q_i$	[-]	CERC (USACE, 1984)	Bruun (1962)

The reduced complexity models discussed above primarily focus on cross-shore processes, where shoreline position serves as a proxy for beach state under the assumption of longshore uniformity. However, this simplification becomes inadequate for embayed beaches that experience significant seasonal rotation or locations with complex longshore transport patterns. Recognizing these limitations, researchers have developed more comprehensive reduced complexity models that incorporate both cross-shore and longshore processes while maintaining computational efficiency. Table 2.1 summarizes key reduced complexity models and their treatment of various coastal processes, where shoreline changes are expressed in differential form on the left side of the equations. This evolution reflects the ongoing effort to balance model complexity with practical applicability, where additional physical processes are incorporated while preserving the fundamental advantages of reduced complexity approaches, i.e., their computational efficiency and ability to simulate shoreline change over extended temporal scales. The diversity of approaches shown in the table demonstrates how different models prioritize specific processes based on their intended applications and local coastal dynamics.

2.2 Model Calibration

Reduced complexity models, while computationally efficient, require extensive site-specific calibration data to determine their free parameters. For instance, models like ShoreFor rely on calibration parameters such as the response factor (ϕ) and efficiency coefficients (C), which have traditionally been treated as site-specific constants. Splinter et al. (2014) made significant progress in addressing this limitation by analyzing twelve different shoreline datasets to develop a generalized parameterization of these coefficients using dimensionless settling velocity (Ω). However, they acknowledged that these empirical formulations require further refinement and validation with additional datasets.

The assumption of parameter stationarity in shoreline models has been increasingly challenged by recent research. In a seminal study of beach morphodynamics, Wright et al. (1985) observed that even at a single location, Ω varies seasonally with wave conditions, with beaches typically exhibiting more dissipative characteristics during high-wave periods and more reflective behaviors during calm conditions. This observation suggests that model parameters might need to adapt to changing environmental conditions rather than remaining fixed.

The limitations of stationary parameters became particularly evident in Splinter et al. (2017)'s analysis of Gold Coast data, where they observed an order of magnitude change in the equilibrium response factor ϕ (from 1000 to 100 days) before and after 2005.

This dramatic shift, triggered by subtle changes in wave forcing patterns, fundamentally challenges the conventional approach of using time-invariant parameters for long-term shoreline modeling. Similarly, Montaña et al. (2020)'s model blind test revealed that while current equilibrium models effectively capture seasonal variations, they struggle with extreme events and show strong dependence on the calibration period selected.

Recent studies have proposed various approaches to address these limitations. Vitousek et al. (2017) implemented an extended Kalman filter for data assimilation, automatically calibrating model parameters and demonstrating that cross-shore transport accounts for approximately 90% of shoreline variability. D'Anna et al. (2020) further investigated parameter sensitivity, finding that the efficiency coefficient (c) dominated during high-energy storm conditions, while the linear trend parameter (b) became the primary source of uncertainty during calmer periods and over longer timescales. The beach response factor (ϕ) showed relatively low sensitivity despite its large variability. The study found that these parameters were strongly influenced by wave energy patterns, with significant seasonal and interannual variations in their contributions to model uncertainty.

Significant advances in non-stationary parameter modeling have emerged through the work of Ibaceta et al. (2020), who integrated a dual state-parameter ensemble Kalman filter into the ShoreFor model. This approach allows parameters to evolve dynamically, showing particular effectiveness in beaches with seasonally-dominated wave climates. Building on this, Ibaceta et al. (2022) demonstrated that non-stationary model parameters correlate with wave climate variability, revealing negative correlations between all cross-shore parameters and the mean dimensionless fall velocity at 5-year running averages.

The traditional assumption of a linear relationship between erosion and accretion efficiency coefficients ($C^e = rC^a$) has also been questioned. D'Anna et al. (2022) demonstrated this relationship's invalidity over long time periods and emphasized the importance of considering parameter interactions in uncertainty analysis. Furthermore, Alvarez-Cuesta et al. (2021) noted that non-stationary parameters could help models adapt to changes in sediment supply, geological conditions, and climate patterns.

These findings collectively suggest that the next generation of shoreline models should incorporate dynamic parameter calibration methods. Such approaches would not only improve prediction accuracy but also provide insights into how beaches respond to varying wave conditions across different timescales. It's important to note that observed parameter variability might also compensate for processes not explicitly included in the models, such as longshore transport and cusp migration, highlighting the need for careful interpretation of parameter evolution.

2.3 Research objectives

The overarching goal of this thesis is to improve our understanding of beach morphodynamics and develop more reliable shoreline predictions under climate change conditions. This goal is pursued through three specific objectives:

- To investigate and quantify beach morphodynamic behavior across multiple temporal scales, from daily storm response to inter-annual variations, using advanced signal processing techniques.
- To develop an improved equilibrium shoreline model by incorporating wave-calibrated non-stationary parameters, enhancing the model's capability to capture both seasonal variations and extreme events.
- To evaluate potential changes in shoreline behavior under future climate scenarios by applying the improved model with wave climate projections from global climate models.

These objectives are systematically addressed through analysis of Hasaki Beach's unique 33-year dataset. Chapter 3 establishes the foundation by characterizing the study site conditions and available measurements. Chapter 4 examines beach morphodynamic behavior from daily storm response to inter-annual variations using advanced signal processing techniques. Chapter 5 develops an improved equilibrium shoreline model incorporating non-stationary parameters calibrated to wave conditions, enhancing capture of extreme events and shoreline variability. Finally, Chapter 6 applies this refined model to evaluate future shoreline changes under climate change scenarios, specifically examining how projected changes in wave climate might affect shoreline variability by the end of the century.

Chapter 3

Description of Hasaki Beach dataset and site conditions

3.1 Beach status

Hasaki Beach, located in eastern Japan and facing the Pacific Ocean, is a longshore uniform sandy beach extending 16 km (Figure 3.1 (a, b)). The beach is fully exposed to wave energy, as it is not sheltered by any hydraulic structures. While there are several groynes built a few kilometers away from the observation point, they do not significantly disturb the alongshore sediment transport, allowing the beach to be treated as longshore uniform. The Hasaki Oceanographical Research Station (HORS, location: 35.84°N, 140.76°E), constructed in 1986, includes a 427-meter-long pier extending seaward and an office building situated directly behind the pier. The station is managed by the Port and Airport Research Institute (PARI), Japan, and serves as a critical facility for coastal and oceanographic research.

Bathymetry data at Hasaki Beach is measured every 5 meters from -115 m (landside end) to +385 m (offshore end) using the plumb line method on the pier by engineers (Figure 3.1(c, d)). Positive values indicate the seaward direction. Measurements from -115 m to 0 m cover both the emerged beach and the nearshore area, providing a comprehensive profile of the beach, and from 0 m to +385 m the submerged upper shoreface containing the whole surf zone is measured. The plumb line measurement method provides high-precision data with an uncertainty of approximately ± 5 cm in the vertical direction. Given the typical beach slope of 1/20 in the study area, this translates to a horizontal shoreline position uncertainty of around ± 1 m. This measurement accuracy is notably superior to alternative shoreline detection methods such as satellite imagery (± 5 m uncer-

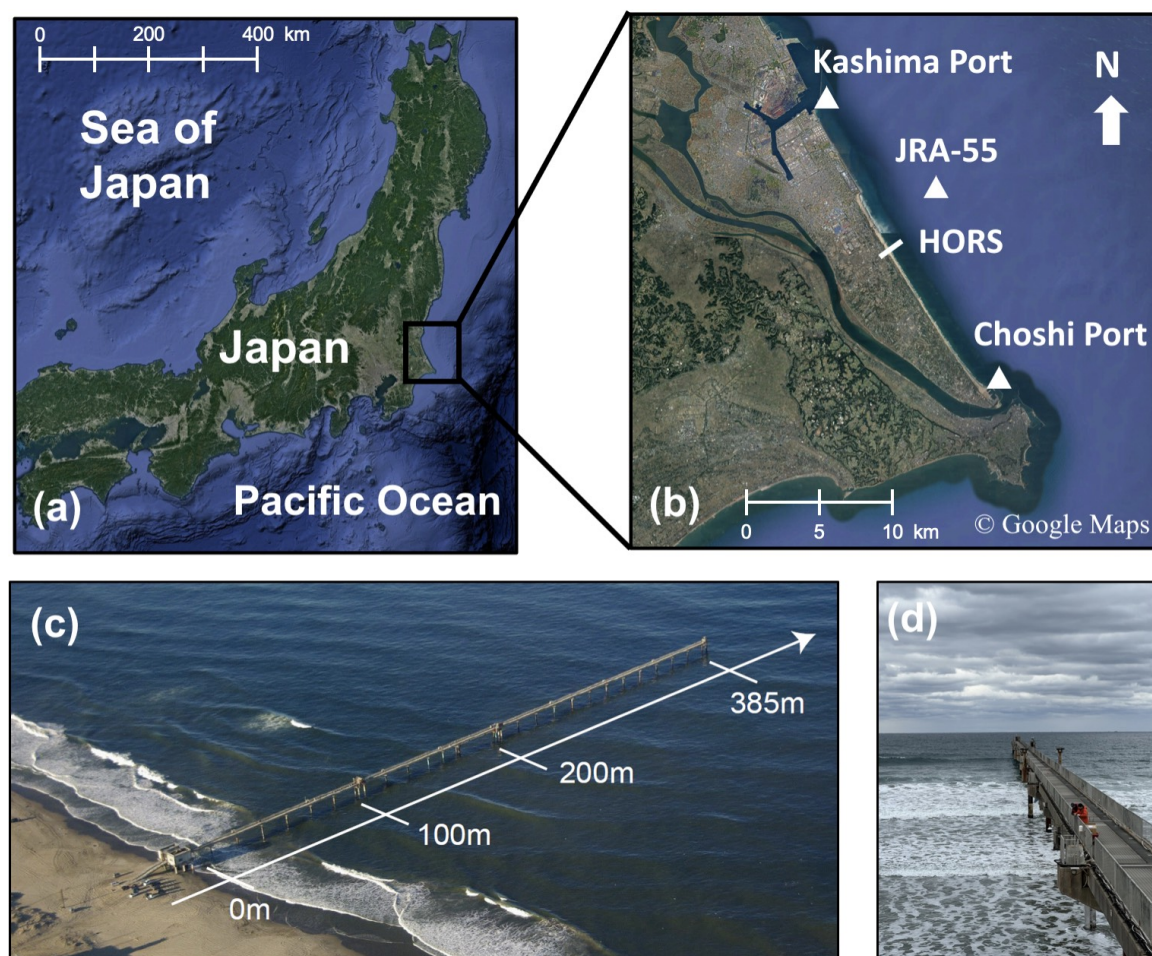


Fig. 3.1 Overview of the Hasaki Oceanographical Research Station (HORS) location and features. (a,b) Satellite image of Japan showing the location of Hasaki Beach, the Hasaki Oceanographical Research Station (HORS) pier and JRA-55 wave data grid point (Adapted from Google Earth (2024)). (c) Aerial photo of HORS pier with distance markers. (d) Engineers measuring bathymetry on December 19, 2023. (Photo by the author.)

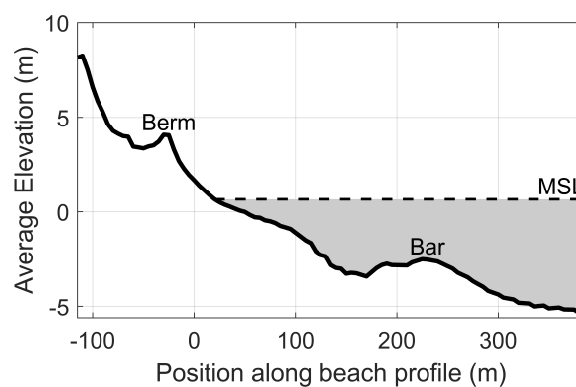


Fig. 3.2 Yearly average shore profile of Hasaki Beach in 2018.

tainty) and camera-based measurements (± 2 m uncertainty). The high precision of these measurements provides increased confidence in subsequent morphodynamic modeling efforts and enables detailed analysis of beach profile evolution at various temporal scales. The sampling frequency for these measurements was daily from 1986 to 2011 and then extended to weekly from 2011 onwards (Figure 3.3(a)). The elevation measured at Hasaki Beach is referenced to the Hasaki datum line (T.P. -0.687 m). The 2018 shore profile (Figure 3.2) shows a berm just above mean sea level (MSL) on the upper beach and a bar at a depth of approximately 3 meters. The berm and bar shift in response to the hydrodynamic environment, such as waves and water levels, creating a dynamic sediment system. The sediment at Hasaki Beach consists of fine sand with a median grain size (d_{50}) ranging from 0.1 to 0.2 mm (Banno et al., 2013).

The shoreline position, defined as the point where the upper shoreface meets the water surface, was analyzed on a monthly average basis from 1986 to 2018. The median shoreline position demonstrates a clear seasonal pattern, reaching its farthest offshore extent in August and retreating to its closest onshore positions in March and October. September exhibits the widest range in shoreline position distribution, indicating the greatest variability, while December and January show the narrowest range, reflecting the most stable shoreline positions during these months.

Additionally, Kashima Port was constructed in 1964, located 7 km north of the northern end of Hasaki Beach. Approximately 50 million m^3 of sediment dredged from Kashima Port was deposited between Kashima Port and Hasaki Beach at a constant rate from 1965 until 1977, which was the only instance of beach nourishment. At the southern end of Hasaki Beach, the Tone River flows into the Pacific Ocean, bringing sediment. Longshore transport is northward from spring to summer and southward from autumn to winter, driven by dominant waves.

3.2 Hydrodynamic conditions

3.2.1 Wave condition

In-situ wave data is collected in the offshore area of Kashima Port, part of Japan's Nationwide Ocean Wave Information Network for Ports and Harbours (NOWPHAS), using a bottom-mounted ultrasonic wavemeter (Figure 3.1(b)). The in-situ wave data is available from 1985 and the sampling frequency is 2 hour. However, this data is not available for the entire study period and there are months to years have no data recorded. To fill this gap, we use long-term wave hindcast data from the JRA-55 atmospheric reanalysis model,

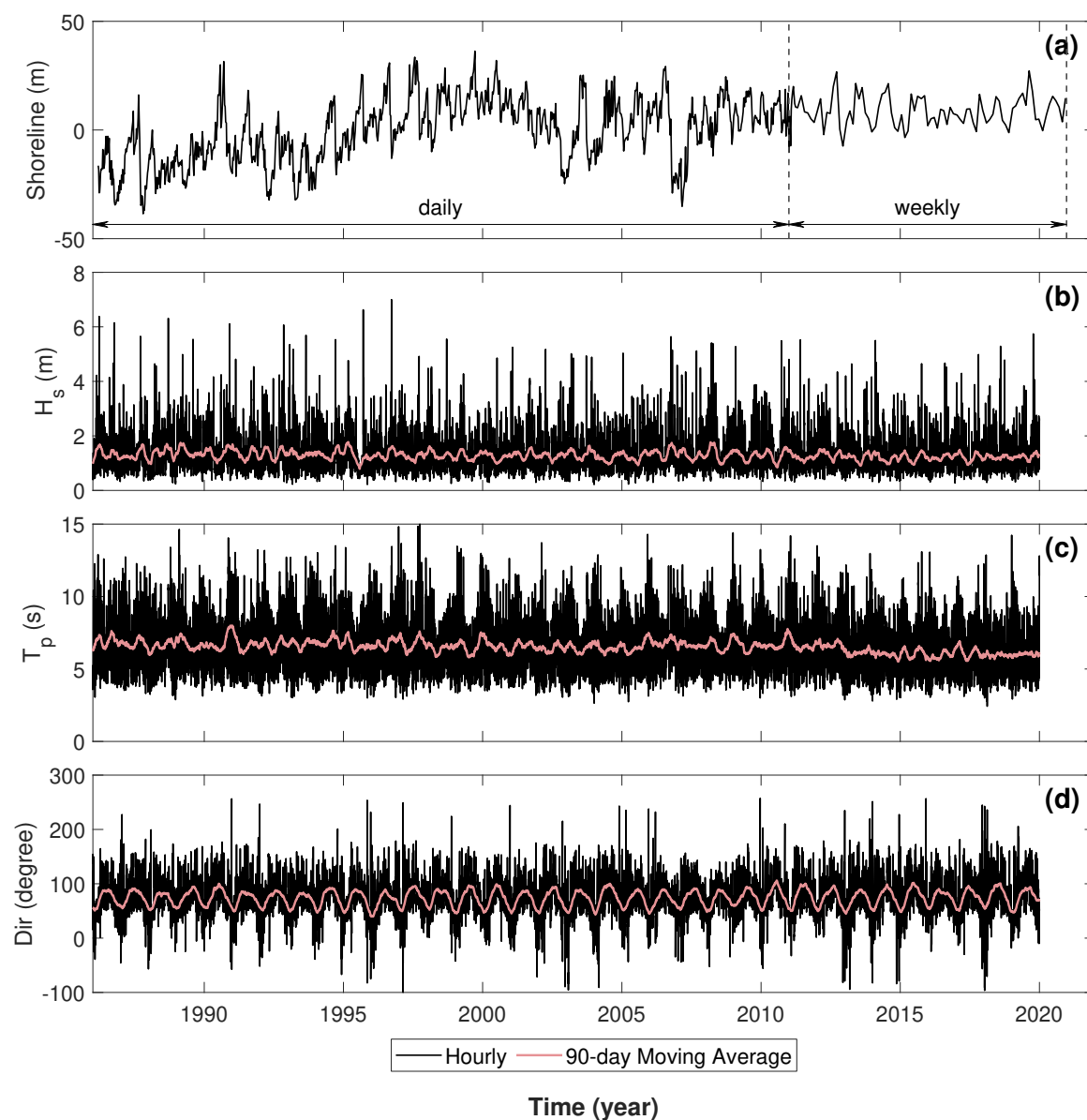


Fig. 3.3 Time series of shoreline and wave conditions, including 90-day moving averages. (a) Shoreline position at Hasaki Beach (positive values indicate movement in the offshore direction); (b) Hourly significant wave height; (c) Hourly wave period; (d) Hourly wave direction. Panels (b-d) display hourly data and 90-day moving averages derived from JRA-55 wave data. All panels show hourly data (black line) and a 90-day moving average (red line).

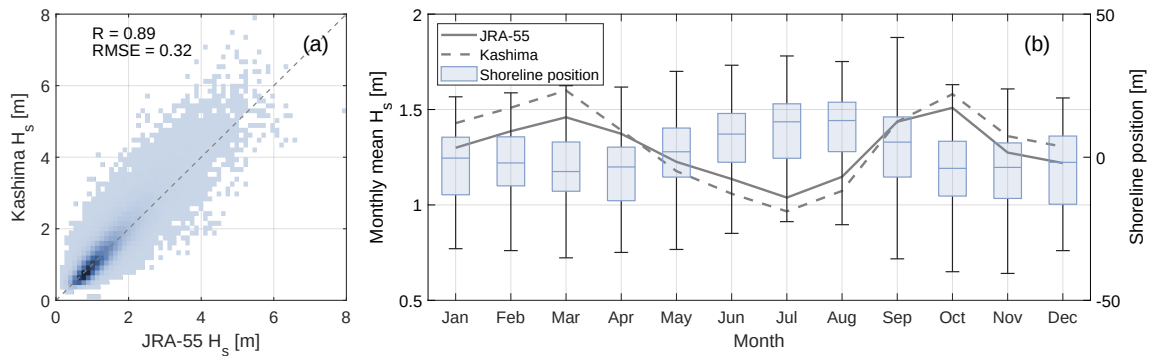


Fig. 3.4 Validation of JRA-55 wave data and monthly variability of wave and shoreline conditions. (a) Comparison between JRA-55 wave hindcast and in-situ wave data at Kashima Port, showing a density scatter plot. (b) Monthly mean significant wave height of JRA-55 and in-situ wave data at Kashima Port (left axis) and boxplots of the distribution of shoreline position by month at Hasaki Beach (right axis).

which has a spatial resolution of 0.067° near Japan's coastal area (Shimura and Mori, 2019). The six-hourly surface wind data and monthly sea ice field calculated by JRA-55 were used as forcing term in WAVEWATCH III to calculate the wave data. The JRA-55 wave data is available from 1979 to the present seamlessly, and we use data from the nearest extraction point (35.87°N , 140.8°E) to Hasaki Beach for this study (Figure 3.1 (b)). This wave data includes significant wave height, wave period, and wave direction, with a temporal resolution of 1 hour (Figure 3.3(b-d)). The average significant wave height is 1.29 m, and the average wave period is 6.57 s. The wave direction is primarily from ENE in winter and from E to ESE in summer.

A comparison between the JRA-55 wave hindcast and the in-situ wave data at Kashima Port shows good agreement, with a correlation coefficient of 0.89 (Figure 3.4(a)). Although the JRA-55 data slightly underestimates the significant wave height (H_s) in the monthly averages, it still reliably represents wave conditions and their seasonal variations. More importantly, the seamless time series wave data provide us the possibility to analyze the time scale and its correlation with shoreline change.

Storminess at Hasaki Beach was investigated following storm classification based on wave height and duration (Dolan and Davis, 1992). Five different wave height thresholds and five durations were used to classify storm events using JRA-55 wave data from 1979 to 2019. The resulting number of storm events is illustrated in Figure 3.5. At this storm-dominated coastline, only one storm exhibited a height of 3.5 meters lasting over 60 hours, and three storms reached a height of 4 meters, persisting for over 48 hours. Importantly, no storms exceeded 4 meters for a duration longer than 60 hours. Seasonal variations in storminess show two distinctive peaks (Figure 3.6), with three different storm

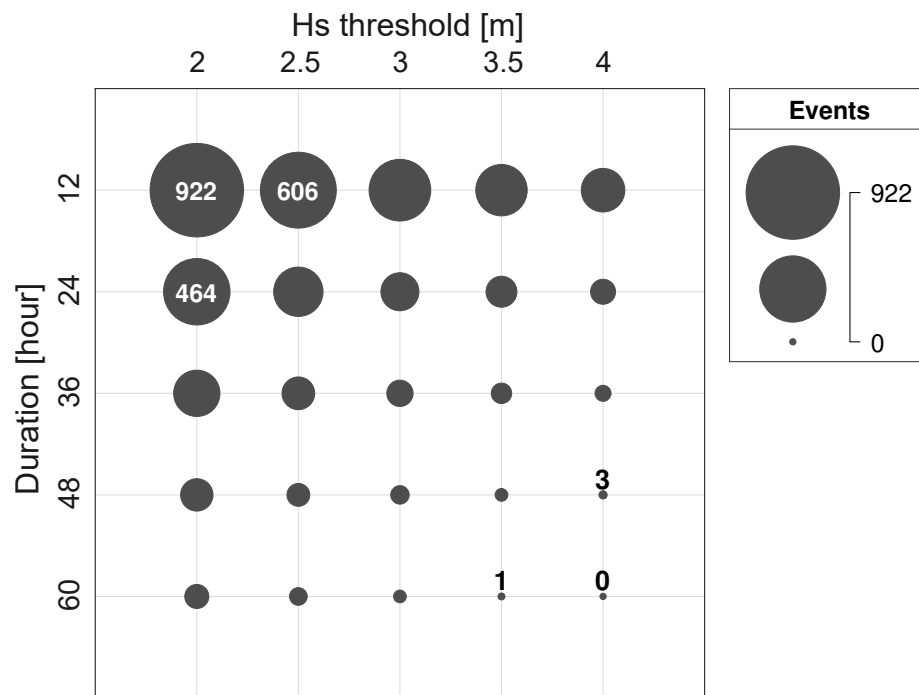


Fig. 3.5 Bubble chart representing the number of storm events for different Wave height thresholds and durations.

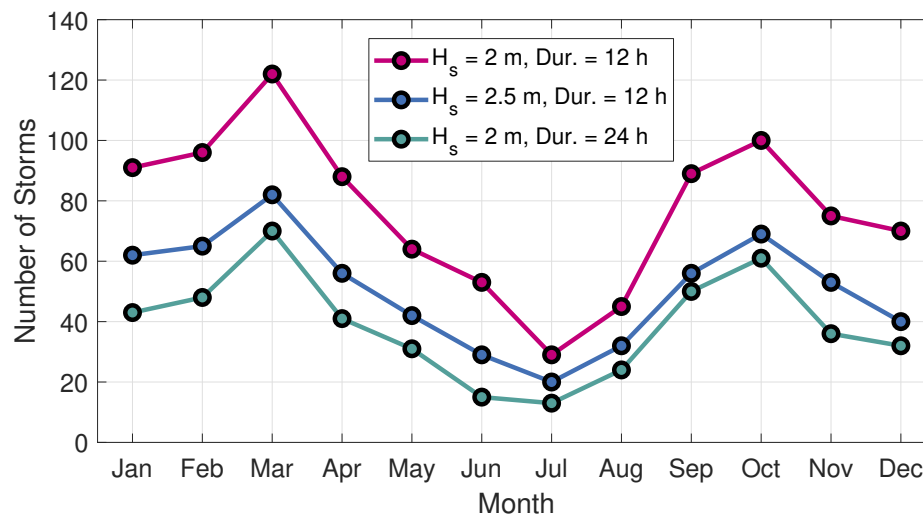


Fig. 3.6 Monthly distribution of storm events for various wave height thresholds and durations.

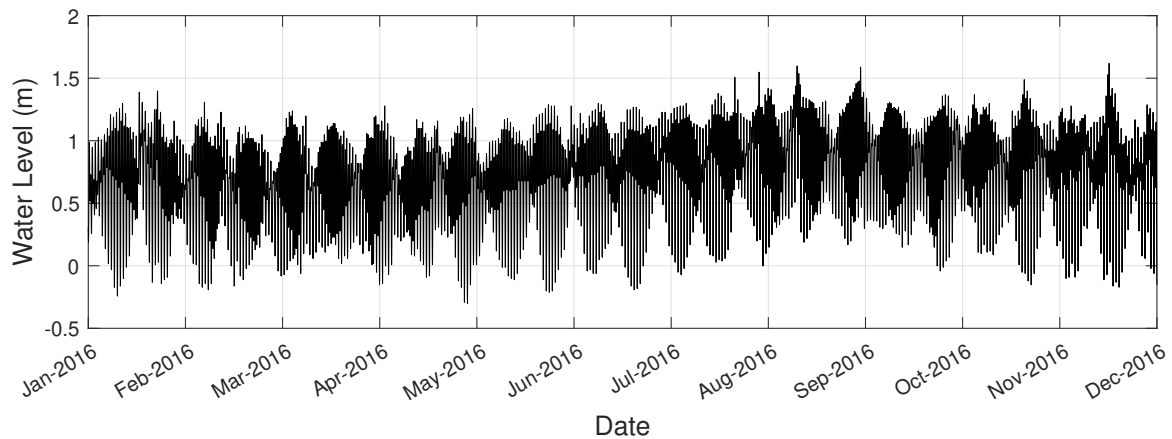


Fig. 3.7 Water level records at Choshi Port in 2016

classifications showing similar trends across the year. The primary peak occurs in March due to explosive extratropical cyclones formed in winter moving southward along the Japanese coast, as evidenced by the cluster analysis of winter cyclone tracks (Mori et al., 2017). A secondary peak appears in October due to the influence of typhoons affecting the region. July exhibited the fewest storms, aligning with the pattern of monthly average significant wave heights.

Monthly comparisons of shoreline and wave data indicate a negative correlation between significant wave height and shoreline position (Figure 3.4(b)). Two peaks in wave height are observed annually, in March and October, during which the median shoreline position reaches its most onshore extent, indicating erosion. The shoreline shifts landward under high wave conditions and returns seaward during low wave conditions, aligning with typical episodic patterns of beach erosion and accretion as described by Wright (1977) (Wright and Thom, 1977).

3.2.2 Tidal condition

The water level data utilized in this study were recorded at a tidal gauge station located near Choshi Port, approximately 12 km southeast of HORS (Figure 3.1(b)). These data have been collected by the Japan Meteorological Agency since 1931, with measurements taken at an hourly frequency, though occasional gaps exist on some dates due to missing data. A harmonic analysis of the water level was conducted using the MATLAB toolbox `t_tide` (Pawlowicz et al., 2002), based on a continuous one-year dataset from 2016. The analysis identified the eight largest tidal constituents, as presented in Table 3.1. The semi-diurnal constituent, M2, has the largest amplitude, confirming that the tidal pattern at Hasaki Beach is predominantly semi-diurnal.

Table 3.1 Tide Analysis Results at Choshi Port

Constituent	Amplitude (m)	Frequency (cpd ¹)	SNR ²
M2	0.3034	1.9323	2.1395×10^4
K1	0.2360	1.0027	1.2526×10^4
O1	0.1897	0.9295	5.3380×10^3
S2	0.1440	2.0000	6.0293×10^3
P1	0.0772	1.0027	1.8561×10^3
Q1	0.0405	0.8932	321.6273
N2	0.0400	1.8950	462.7484
K2	0.0399	2.0000	231.5957

¹ Cycle per day² Signal-to-Noise Ratio. A higher SNR indicates a more reliable tidal constituent with lower uncertainty in its measurement.

The original datum level at Choshi Port is -1.769 m. For better interpretability and to facilitate comparisons with beach elevation, the water level data were adjusted to align with Hasaki Beach's datum, which is -0.687 m. The recalibrated water level time series is shown in Figure 3.7, displaying a MSL of 0.65 m, a mean high water level (MHW) of 1.25 m, and a mean low water level (MLW) of -0.2 m (Banno et al., 2020). The resulting tidal range of 1.45 m classifies Hasaki Beach as a micro-tidal environment, as indicated in Table 3.2.

Table 3.2 Tidal Range Classifications

Classification	Tidal Range (m)
Micro-tidal	< 2 m
Meso-tidal	2–4 m
Macro-tidal	> 4 m

Chapter 4

Analysis of morphodynamic behaviors of Hasaki beach

4.1 Overview of beach morphological behavior

Hasaki Beach is a dynamic coastal system where the interplay of natural processes constantly reshapes its morphology. The interaction between wave action, tidal currents, and sediment transport leads to the continuous formation and alteration of its dunes, berms, and bars. This shifting landscape is not merely a random occurrence; rather, it represents a state of dynamic equilibrium, where the various components adapt in response to hydrodynamic changes. Seasonal fluctuations, such as increased storm activity during winter months, can significantly impact beach profiles. Understanding these processes is crucial for developing effective shoreline modeling. In this section, the behaviors of the berm and bars will be discussed in detail.

4.1.1 Berm and shoreline

A beach berm is a nearly horizontal, shore-parallel ridge formed on the beach by the landward movement of the coarsest beach material during wave uprush. This feature is evident in the Hasaki Beach profile (Figure 3.2). Typically, berms form during calm wave conditions and erode under high wave energy. Understanding this morphodynamic behavior is critical for coastal models because it determines which shoreline reference level best represents the target morphodynamic change near berm.

According to Castelle et al. (2014), equilibrium models are highly sensitive to the chosen reference level. Using MHW as the reference reduces noise from sediment fluctuations and more accurately connects shoreline changes to incident wave energy. However, some

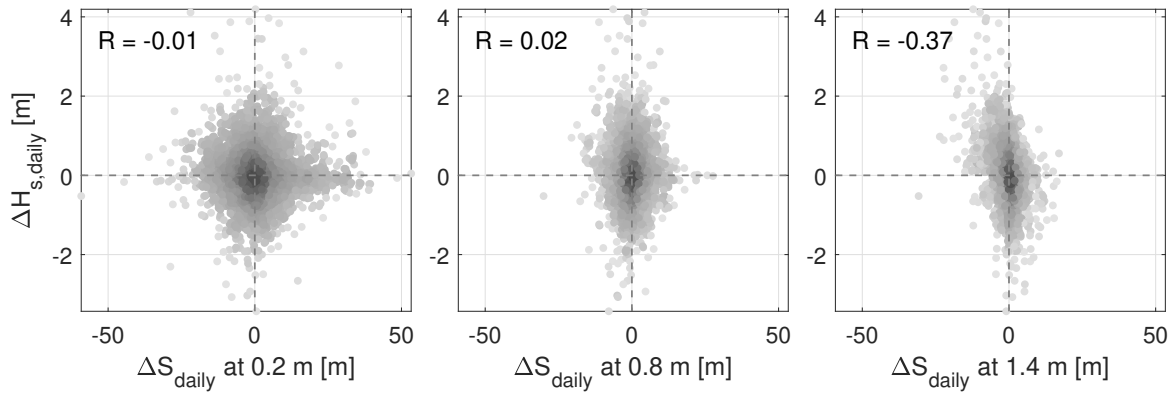


Fig. 4.1 Scatter plots illustrating the relationship between daily changes in significant wave height ($\Delta H_{s,daily}$) and daily changes in shoreline (ΔS_{daily}) at three different reference levels (0.2 m, 0.8 m, and 1.4 m).

beaches, such as the Gold Coast in Australia, still use MSL as a reference for shoreline position (Splinter et al., 2014). Generally, it is not advisable to set the reference level below MSL, as accumulation at lower elevations can lead to misleading interpretations of shoreline changes. 4.2 illustrates an important example of how small changes in beach morphology can significantly impact shoreline position measurements. The observation from September 11-12, 2000 shows that while the overall beach profile and sediment volume remained largely stable across these two days, the shoreline position (measured at the 0.2 m elevation contour) appeared to shift landward by approximately 50 m. This dramatic apparent movement was not due to actual beach erosion, but rather resulted from minor sediment accumulation between the 0.2 m and 0.4 m elevation contours, as shown in the inset figure. This example highlights how sensitive shoreline position measurements can be to subtle changes in beach topography near the measurement elevation.

The intertidal zone is highly dynamic. To understand the relationship between shoreline and wave height, we examined shoreline changes and wave height variations at daily intervals across three different reference levels (Figure 4.1). No significant correlation was found between wave height and shoreline change at the 0.2 m and 0.6 m levels. However, at the 1.4 m level, equivalent to MHW with an additional 0.15 m of wave run-up, a negative correlation appeared with a correlation coefficient of -0.37. This indicates that higher berm areas are more influenced by wave energy: higher waves lead to erosion, while calmer waves promotes swash deposition. In contrast, in lower areas, high waves both remove sand and deposit new sediment from the upper berm, resulting in a mix of erosion

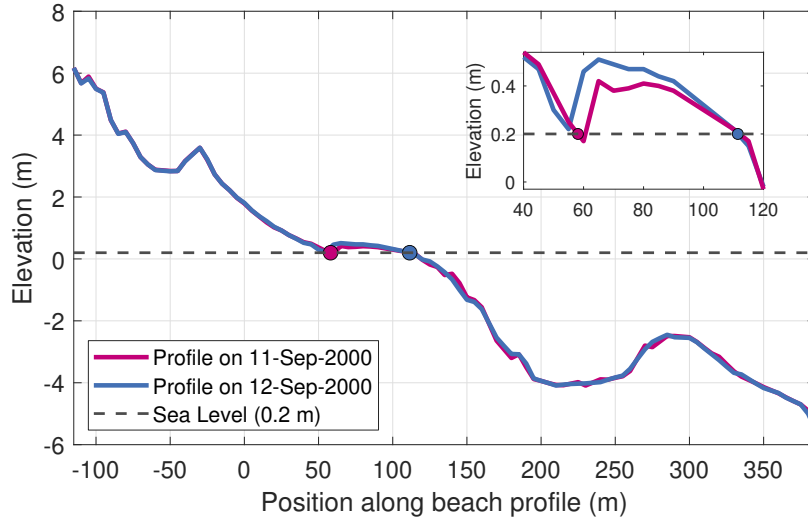


Fig. 4.2 The beach profile on 11 September, 2000 and 12 September, 2000. Circle markers represent the calculated shoreline positions.

and deposition. Given these findings, a reference level of 1.4 m is used for the shoreline in subsequent analyses.

Shoreline positions are compared with four wave parameters: significant wave height (H_s), peak wave period (T_p), dimensionless settling velocity (Ω), and wave power (P). These parameters are calculated using daily averaged data and are defined by the following equations:

$$\Omega = \frac{H_s}{wT_p} \propto H_s/T_p \quad (4.1)$$

$$P = EC_g \propto H_s^2 T_p \quad (4.2)$$

where: P is the wave power (Watts), T_p is the peak wave period (s), w is the settling velocity of on-site sediment (m/s), $E = 1/16\rho g H_s^2$ is the significant wave energy (N/m), and C_g is the wave group velocity (m/s). Figure 4.3 displays shoreline position's correlations with four wave parameters, with values averaged by month to indicate seasonal variations. This analysis compares the shoreline position with wave parameters at two temporal scales. At the daily scale, wave parameters are first averaged daily, while at the weekly scale, a 7-day moving average is applied to smooth out high-frequency fluctuations. For each temporal scale, the correlation coefficient is computed for each day using the processed wave data and corresponding shoreline position, then these daily correlation values are averaged within each month to reveal seasonal patterns. Significant wave height H_s and dimensionless settling velocity Ω both display a similar negative correlation with shoreline position, ranging from -0.1 to -0.5. In contrast, the wave peak period T_p shows a weaker

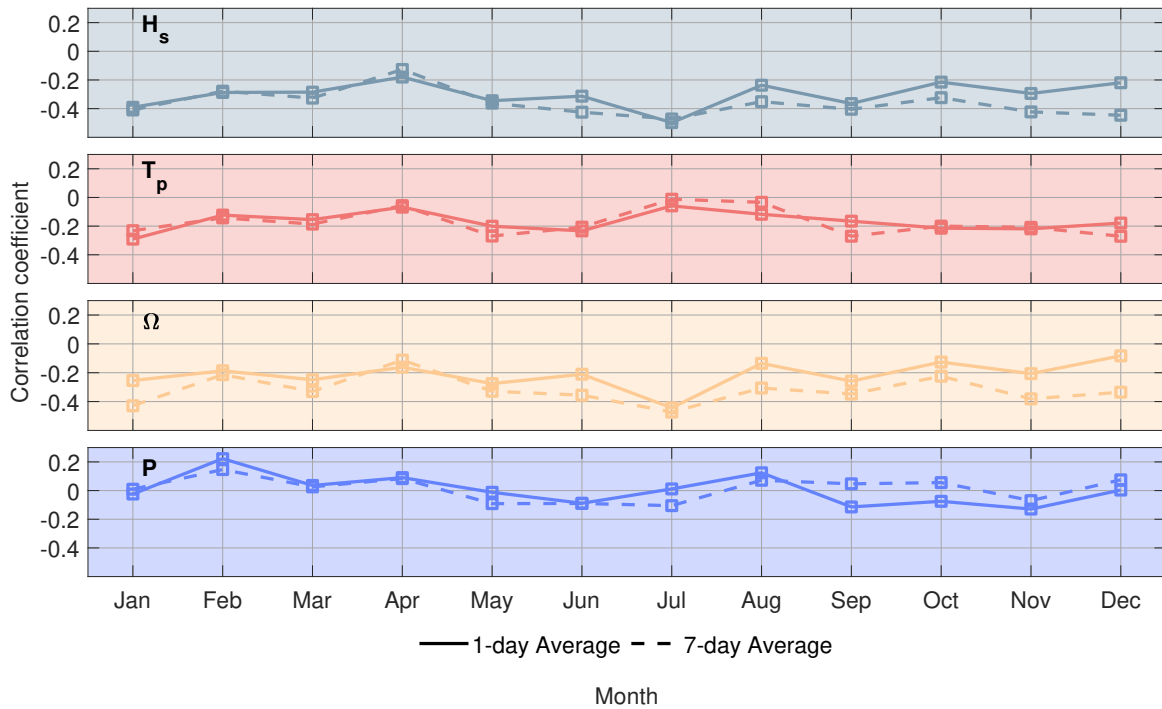


Fig. 4.3 Monthly averaged correlation between shoreline position and four wave forcing variants over different average period

negative correlation, with values between 0 and -0.3. The correlation between wave energy P and shoreline position is minimal, fluctuating around 0, with values ranging from 0.2 to -0.2.

Combining this with the monthly averaged significant wave height (Figure 3.4(b)), the correlations of H_s and Ω reach their maximum in July when the wave height is at its lowest. Conversely, the correlations of H_s and Ω are lowest in March, one of the months with the highest wave heights. Using the moving mean method, the correlations of H_s and Ω in the weekly case show higher values compared to the daily case, while the correlation of P continues to fluctuate around 0.

Finally, the relationship between wave heights and shoreline change was analyzed through probability density functions of daily shoreline changes under different wave height conditions (Figure 4.4). Under low to moderate wave conditions ($H_s < 2$ m), the distributions show a tendency toward accretion ($\Delta S > 0$), while higher wave conditions ($H_s \geq 2$ m) are associated with shoreline retreat ($\Delta S < 0$). This erosive tendency becomes particularly pronounced during high-energy conditions ($H_s \geq 3$ m), where the probability distribution shows a clear negative skew, indicating increased likelihood of significant shoreline retreat.

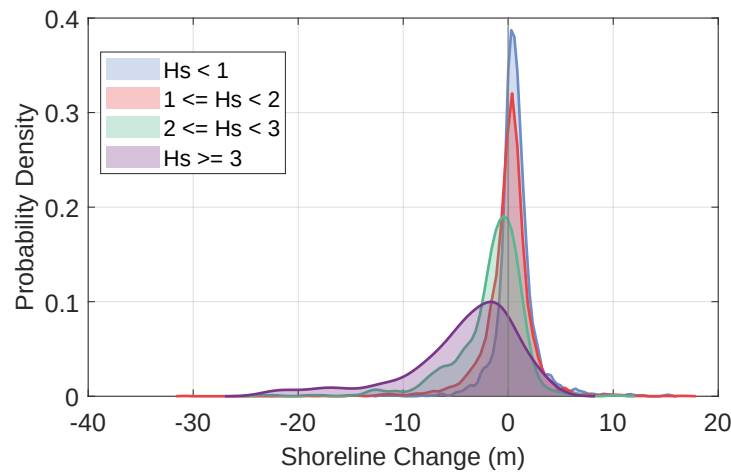


Fig. 4.4 Probability density function of daily shoreline change under different daily averaged significant wave height conditions.

Table 4.1 Shoreline Change Statistics for Different H_s Groups

H_s Group	Mean (m)	Std (m)
$H_s < 1$	0.71	1.94
$1 \leq H_s < 2$	-0.03	2.46
$2 \leq H_s < 3$	-1.67	3.40
$H_s \geq 3$	-4.23	5.41

Overall, under low wave conditions ($H_s < 1$ m) and moderate wave conditions ($1 \leq H_s < 2$ m), the probability density functions (PDFs) indicate that shoreline accretion is the most probable accrete, as evidenced by the positive peak values. However, as wave heights increase, the shoreline becomes more likely to erode, with the PDF peaks shifting to negative values under higher wave conditions. The mean shoreline change provides further insight into this trend. Under moderate wave conditions ($1 \leq H_s < 2$ m), while the shoreline is most likely to accrete, the mean value is slightly negative ($\mu = -0.03$ m). This is accompanied by an increase in standard deviation ($\sigma = 2.46$ m), reflecting greater variability in shoreline behavior as wave energy increases.

Under high wave conditions ($2 \leq H_s < 3$ m and $H_s \geq 3$ m), the distributions exhibit a pronounced negative skew, indicating that more severe erosion events become increasingly likely. For $2 \leq H_s < 3$ m, the mean shoreline change is -1.67 m with a standard deviation of 3.40 m, while for $H_s \geq 3$ m, the mean change is -4.23 m with a standard deviation of 5.41 m. This skewness, combined with the larger standard deviations, under-

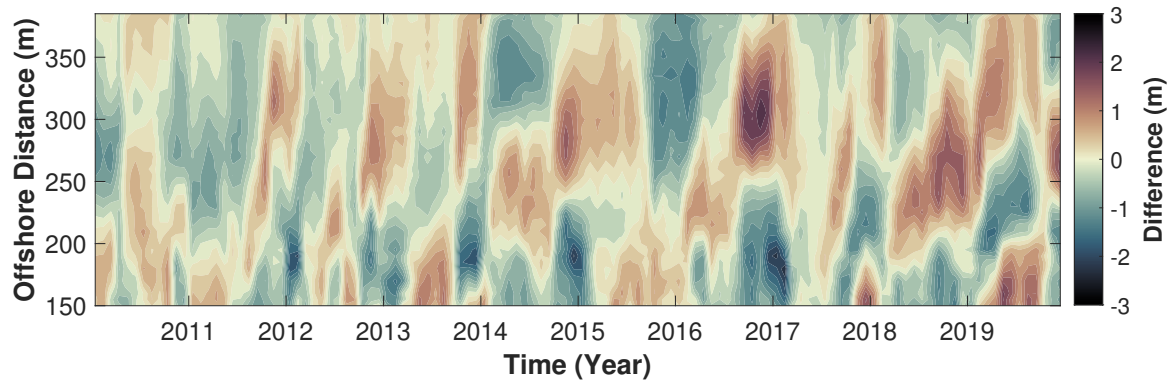


Fig. 4.5 Spatiotemporal variation of beach profile deviations from the 10-year mean at Hasaki Beach during 2010-2019. Color scale indicates elevation differences from the mean profile in meters.

scores the heightened potential for significant shoreline retreat during high-energy wave conditions.

4.1.2 Bar movement

Hasaki Beach typically features a one-bar system with a trough-bar morphology. Figure 4.6 illustrates sandbar movement driven by seasonal wave height variations at Hasaki Beach from 2016 to 2019. In July, when wave heights are at their lowest, the beach profile typically shows sediment accumulation near the shore, creating a more elevated nearshore profile. By October, when wave heights reach their annual peak, the increased wave energy causes erosion of the nearshore profile and redistributes sediment offshore. This offshore bar movement occurs as higher waves break at a more offshore position, pushing sediment further seaward.

However, a longer-term analysis reveals that the predominant bar movement is consistently seaward. Figure 4.5 illustrates this pattern through a contour map of profile deviations from the 10-year mean (2010-2019), where warm colors indicate elevated areas (bar crests) and cool colors indicate depressions (troughs). The figure clearly shows a cyclic pattern where bars form near the 150m offshore position, gradually migrate seaward over time, and eventually diminish at the offshore end of the observation area. As one bar moves offshore and dissipates, a new bar forms near the 150m position, initiating the next cycle. This pattern is consistent with the findings of Kuriyama (2002), who documented through an 8-year study from 1987 to 1994 that bars at Hasaki undergo a continuous seaward migration with an approximate one-year cycle. While the bars consistently migrate seaward, the underlying sediment transport processes are more complex. Sediment moves

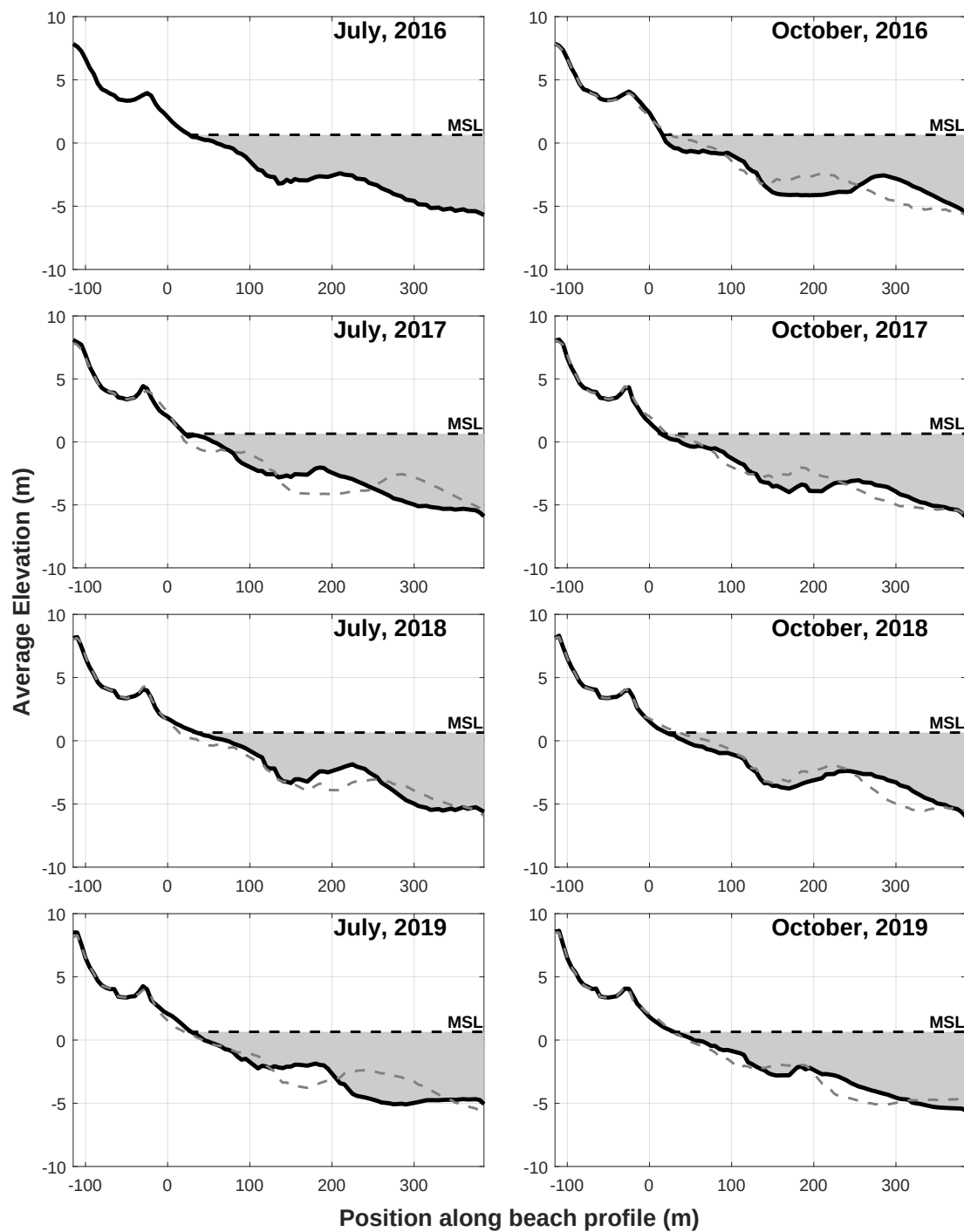


Fig. 4.6 Averaged beach profile in July and October from 2016 to 2019. The solid line shows the present beach profile and dash line shows the beach profile in the previous figure for comparison.

both seaward and shoreward, with seaward transport occurring primarily on and around bar crests and shoreward transport in the trough regions. The intensity and direction of sediment transport vary seasonally: from winter to spring, seaward transport dominates, while in autumn, shoreward transport increases in response to different wave conditions.

This understanding of bar behavior at Hasaki Beach demonstrates that while seasonal wave patterns influence sediment transport patterns, the overall morphodynamic evolution involves a consistent seaward migration pattern rather than a simple onshore-offshore oscillation. The beach profile continuously adapts to changing wave conditions through complex patterns of sediment redistribution, with bars exhibiting a cyclic pattern of formation, seaward migration, and eventual dissolution in deeper water.

4.2 Short-term morphodynamic behaviors

In this section, shoreline position is analyzed on a short-term timescale, focusing on variations ranging from daily to weekly intervals. The following section will address long-term trends.

Due to gaps in the beach profile data on weekends, national holidays, and during severe weather events, the shoreline time series is irregularly sampled. This irregular sampling complicates the use of conventional time-scale analysis methods, such as Wavelet Transform or Fourier Transform. To manage this, shoreline position data is averaged monthly to create a uniformly sampled time series (Figure 4.7 (a)). The monthly average shoreline position is assigned to the 15th of each month, and interpolation is used to map these values back to the original measurement dates. By subtracting the monthly averaged data, short-term variations in shoreline position are isolated, as shown in Figure 4.7 (b) and their variance is shown in Table 4.2.

Table 4.2 Variance values for shoreline data

Data Type	Time scale	Variance (m ²)
Original Shoreline	All time scales	209.39
Monthly Average Shoreline	Seasonal to inter-annual	165.37
Short-term Variation	Daily to weekly	17.33

4.2.1 Variance

The shoreline position after applying a monthly average retains primarily inter-monthly and inter-annual variations, capturing most of the variance observed in the original

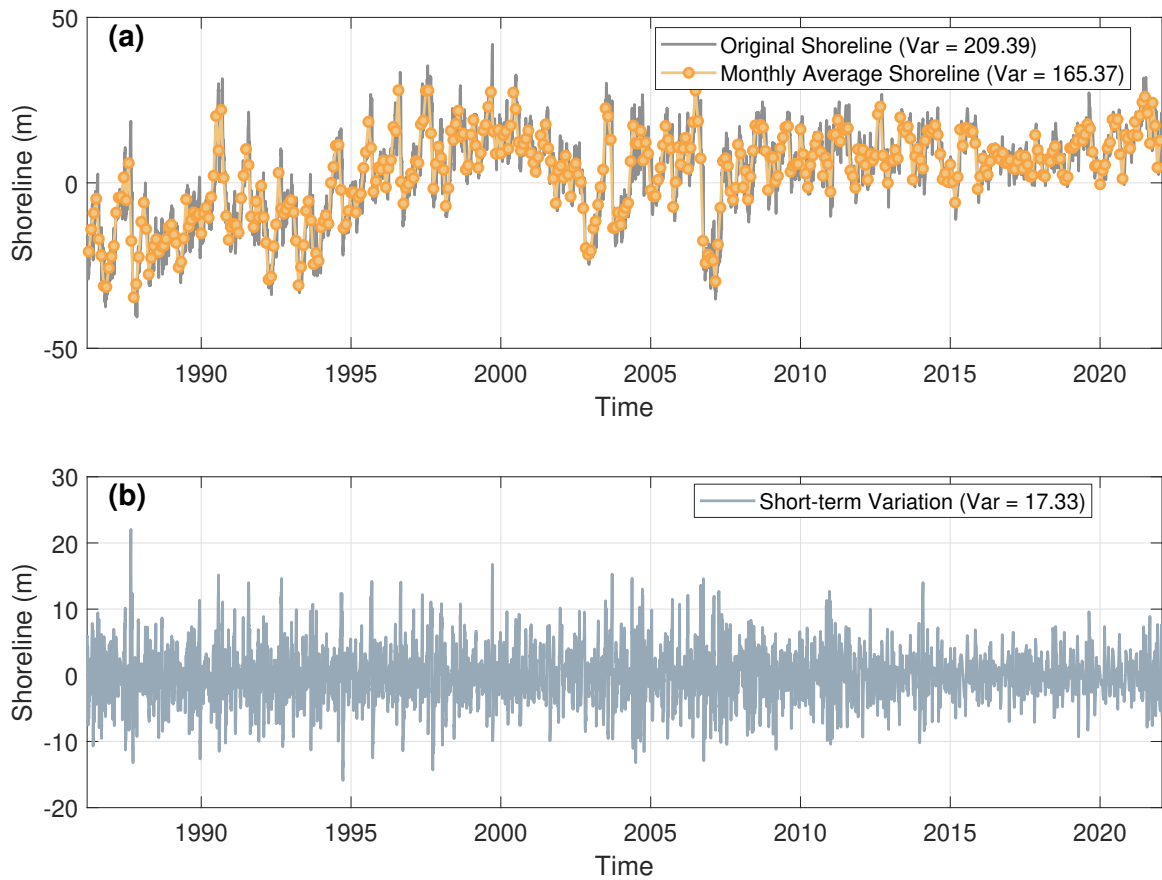


Fig. 4.7 Shoreline position time series decomposition. (a) Original shoreline position data and its monthly averaged representation from 1986 to 2021, with their respective variances. (b) Short-term shoreline position variation derived by removing the monthly average from the original time series, showing the remaining higher-frequency fluctuations.

shoreline data according to Table 4.2. Although the variance of the short-term fluctuations is relatively low compared to the long-term timescale data, significant changes exceeding 10 meters are still quite common as shown in Figure 4.7 (b). To further examine short-term behavior, the variance of these fluctuations was calculated on a monthly basis over the entire study period (Figure 4.8 (a)). The six months with the highest monthly variances are highlighted, with four of these occurrences in September. Consequently, the monthly variance was averaged across all months, as shown in Figure 4.8 (b). This analysis reveals that September and August exhibit the highest and second-highest short-term variances, respectively, with variance levels in these two months being significantly higher than in other months.

Furthermore, the months with the most active short-term shoreline variations are not October and July, which are typically associated with the highest and lowest wave energies,

respectively. Instead, August and September, the transitional months between the calm summer conditions and the high-energy October storms, exhibit the greatest variance. Intuitively, one might expect October, with its peak wave energy and frequent storm events, to have the highest short-term variance. However, October's variance is not significantly different from other months except for August and September. This behavior may be explained by the seasonal sediment dynamics: from March to July, gradually decreasing wave energy allows sediment to accumulate along the upper shoreface, building up the berm in relatively calm conditions. July marks a tipping point, as wave energy begins to increase, mobilizing the abundant fine sediment previously settled in the shoreface. This increase in wave activity in August creates an active environment for sediment transport, similar to the conditions observed in September. Moreover, August and September typically experience fewer storm events than October, allowing more frequent intervals for the shoreline to partially recover between high-energy events, thereby contributing to the higher monthly variance in these two months. In interpreting the short-term shoreline variations, wave energy and sediment availability emerge as the two most critical factors influencing shoreline dynamics on this timescale.

4.2.2 Storm response

As discussed in Section 4.2.1, short-term variability is likely influenced by erosion during high-energy events and subsequent restoration. To better understand this, the daily shoreline change behavior is analyzed.

Unlike the storm classification based on H_s thresholds and duration outlined in Section 3.2.1, this analysis introduces a storm classification based on relative changes in H_s , as we would like to examine shoreline's response to changing wave conditions. The focus is on shoreline behavior during the first two days of storm arrival and post-storm conditions. Given that the maximum sampling frequency for beach profiles is once per day, daily averaged wave heights are used for comparison. The shoreline response during storm arrival and post-storm scenarios is examined for the first two days, as summarized in Table 4.3. For comparison, shoreline changes under stable wave conditions, defined as daily wave height changes of less than 0.5 m, are also analyzed.

Figures 4.9(a) and 4.9(b) illustrate the probability density function (PDF) of shoreline changes during storm arrival and post-storm conditions, with the stable wave scenario included for reference. Under stable wave conditions, the shoreline typically restores at a slow rate of 1 to 2 meters per day, and significant changes exceeding 5 meters in a single day are rare. In Figure 4.9(a), during the first day of storm arrival, the PDF shifts notably towards negative values, indicating increased likelihood of shoreline erosion. On the

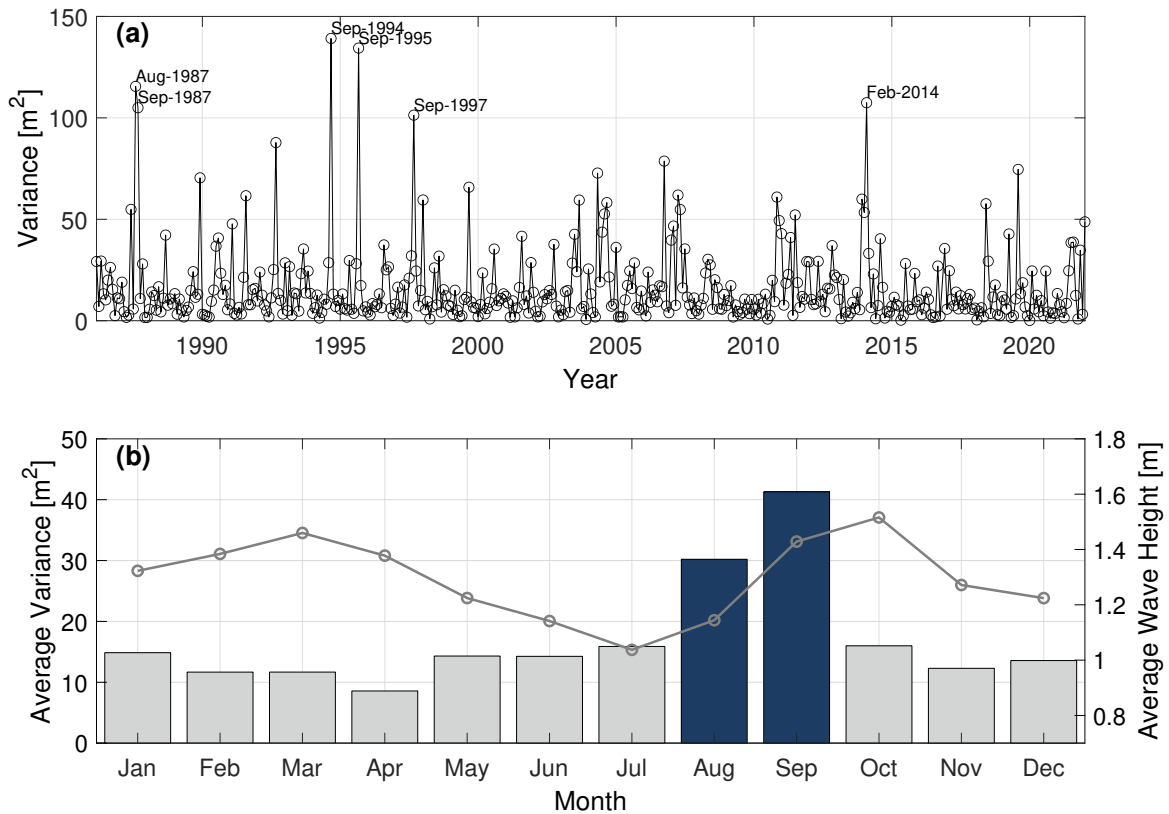


Fig. 4.8 Analysis of monthly shoreline variance and its relation to wave height. (a) Monthly variance in shoreline position calculated from short-term variations over time. (b) Average monthly variance in short-term shoreline position variations (bars) alongside average monthly wave height (line) throughout the year.

second day, despite relatively stable wave heights, the PDF still peaks on the negative side, suggesting continued erosion. For post-storm conditions, as shown in Figure 4.9(b), the PDF on the first day post-storm shifts slightly towards positive values and becomes more dispersed, indicating mild shoreline recovery. By the second day post-storm, the PDF resembles that of stable wave conditions, showing no significant difference in shoreline behavior.

Figure 4.9(c) compares the shoreline change distribution on the second day of storm arrival and post-storm with stable wave conditions. Even though wave intensity remains stable on the second day of storm arrival, erosion continues, but at a slower rate, suggesting that sediment availability has decreased since the first day, and the erosion efficiency gradually decreases. This continued erosion is statistically significant compared to stable wave conditions ($p < 0.001$). In contrast, the shoreline change on the second day post-storm shows no significant difference from stable wave conditions ($p > 0.05$), indicating that post-storm effects on shoreline recovery do not extend beyond the first day.

Table 4.3 Wave conditions of cases

Case	Day 1		Day 2	
	$\Delta H_s(\text{m})$	No. of Case	$\Delta H_s(\text{m})$	No. of Case
Storm arrival	$\Delta H_s \geq 1.0$	253	$-0.5 \leq \Delta H_s \leq 0.5$	87
Post-storm	$\Delta H_s \leq 1.0$	187	$-0.5 \leq \Delta H_s \leq 0.5$	119
Stable wave	$-0.5 \leq \Delta H_s \leq 0.5$	5,139		

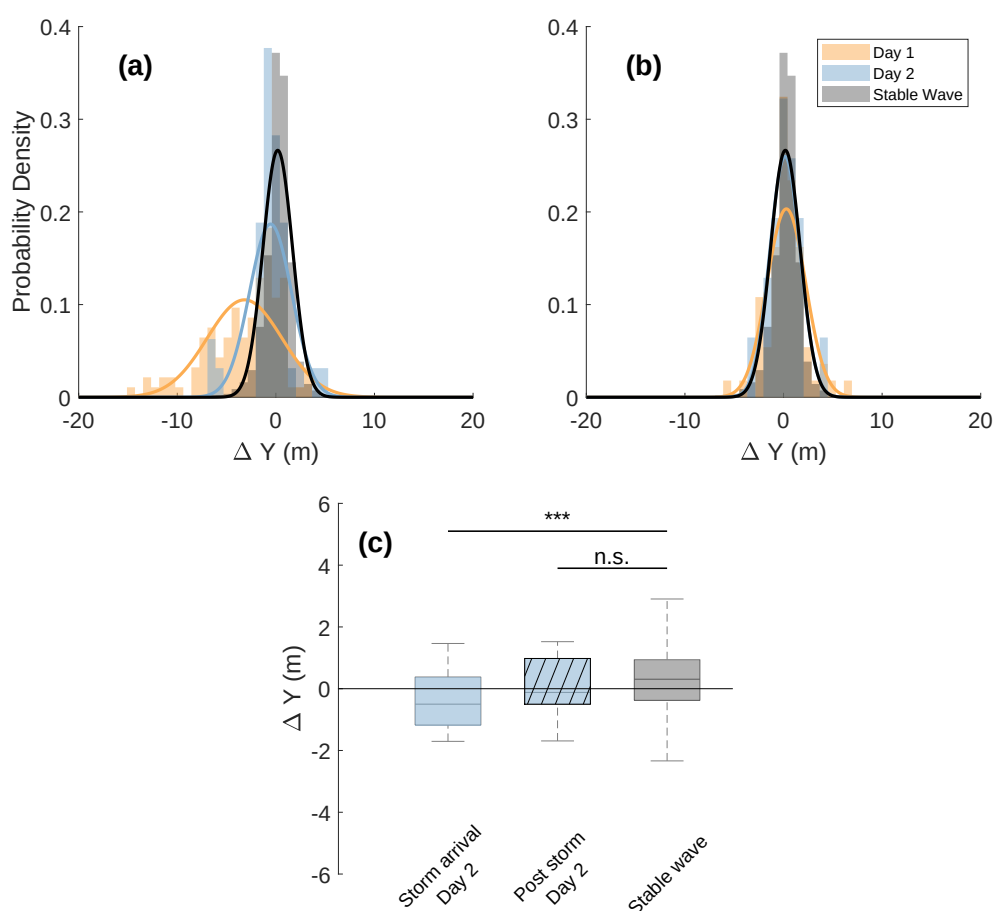


Fig. 4.9 Shoreline change probability distributions and statistical comparison under varying wave conditions. (a) Probability Density Functions (PDFs) of shoreline change on the first and second days of storm arrival, with stable wave conditions as a reference. (b) PDFs of shoreline change on the first and second days post-storm, with stable wave conditions as a reference. (c) Boxplot comparison of shoreline change for storm arrival (Day 2), post-storm (Day 2), and stable wave conditions, with statistical significance indicated.

Overall, shoreline erosion is most intense on the first day of storm arrival, with erosion efficiency gradually decreasing on subsequent days as sediment availability declines. Post-storm conditions can enhance shoreline recovery, but this effect is generally limited to the first day after the storm. Under stable wave conditions, the shoreline tends to recover slowly, with gradual accretion occurring at a low rate. The daily shoreline changes in response to storms explain why the monthly averaged variance of short-term variation peaks in August and September (Figure 4.8). Storms during these months significantly erode the beach, but restoration is a slower, more steady, and long process. Since there are fewer storms in August and September compared to October, the beach has time to recover from storm-induced erosion in between storms. This repeated cycle of erosion and gradual restoration leads to higher short-term variability in these months.

4.3 Long-term morphodynamic behaviors

In this section, the shoreline component with time scale longer than monthly will be analyzed. As the time series shoreline data has been averaged into month consecutively, the conventional methods Wavelet transform and Fourier transform become available to analyze the time scale. In section 4.3.1, the wavelet transform will introduced and in section b., the trend is analyzed by using wavelet. At the end, in Section 4.3.2, the seasonal behavior of shoreline will be analyzed by Fourier transform.

4.3.1 Discrete wavelet transform for time series decomposition

a. Theoretical framework

The analysis of time series data often requires understanding frequency components at different time scales. While Fourier transforms provide frequency information, they lose temporal localization. Following Mallat (2009), wavelet transforms address this limitation by providing both time and frequency localization through a multi-resolution analysis approach. The foundation of wavelet analysis lies in the construction of special functions called wavelets. A wavelet family consists of dilated and translated versions of a mother wavelet ψ :

$$\psi_{j,n}(t) = \frac{1}{\sqrt{2^j}} \psi\left(\frac{t - 2^j n}{2^j}\right) \quad (4.3)$$

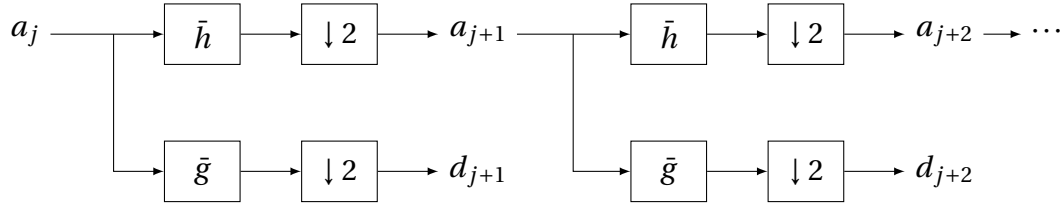


Fig. 4.10 A wavelet transform is computed with a cascade of filterings with $\bar{h}$ and $\bar{g}$ followed by a factor 2 subsampling.

Working alongside the wavelet function is a scaling function ϕ , which handles the coarser approximations:

$$\phi_{j,n}(t) = \frac{1}{\sqrt{2^j}} \phi\left(\frac{t-n}{2^j}\right) \quad (4.4)$$

These functions (Eq. (4.3) and Eq. (4.3)) form orthonormal bases, meaning they are both orthogonal and normalized. This orthonormality is crucial as it allows us to:

- Decompose signals into independent components
- Perfectly reconstruct the original signal from these components
- Efficiently implement the transform through discrete filtering operations

The discrete wavelet transform (DWT) implements this mathematical framework through a practical filtering approach. The relationship between the continuous wavelet transform (CWT) and discrete implementation is established through filter coefficients:

$$h[n] = \left\langle \frac{1}{\sqrt{2}} \phi\left(\frac{t}{2}\right), \phi(t-n) \right\rangle \quad (4.5)$$

$$g[n] = \frac{1}{\sqrt{2}} \left\langle \psi\left(\frac{t}{2}\right), \phi(t-n) \right\rangle \quad (4.6)$$

where $h[n]$ represents the discrete low-pass filter derived from the scaling function, while $g[n]$ represents the discrete high-pass filter derived from the wavelet function. These filters form a conjugate mirror pair, ensuring perfect reconstruction capability. Figure 4.11 shows an example of Daubechies 6 wavelet functions and filters.

Figure 4.10 illustrates a diagram of a cascade of filterings using DWT. a_j is the signal at the subsampling level j . When $j = 0$, a_0 represents the original data. The signal a_j passes through a high-pass filter $\bar{g}$ and a low-pass filter $\bar{h}$ and the high-frequency component d_{j+1} and the residual signal a_{j+1} are calculated. By this cascade filtering, the high-frequency components are separated from the original signal level by level and the biggest advantage of using DWT is the original signal can be perfectly reconstructed by components reversely.

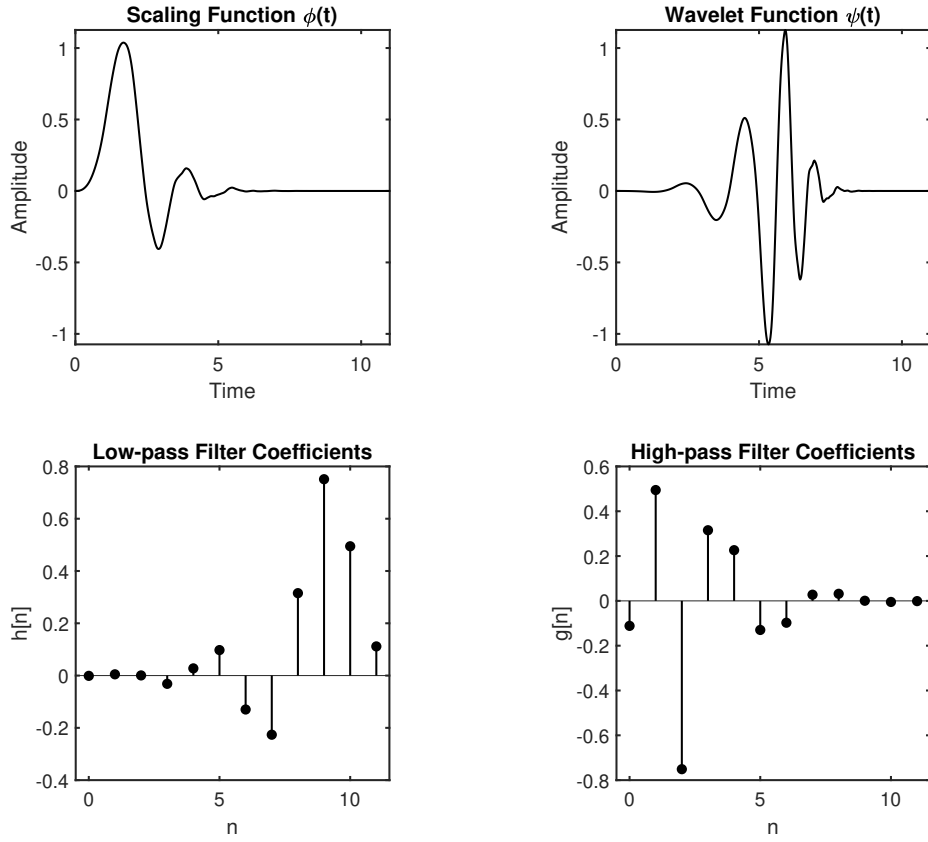


Fig. 4.11 Daubechies 6 (db6) wavelet functions and filters. Scaling function ($\phi(t)$) and wavelet function ($\psi(t)$) are continuous function; low- and high-pass filters are discrete function.

In wavelet transform, a_j is also called *approximation coefficients* and d_j is called *detail coefficients*. For discrete signals, we denote time reversal as $\bar{x}[n] = x[-n]$ and define the downsampling operation as:

$$\check{x}[n] = \begin{cases} x[p] & \text{if } n = 2p \\ 0 & \text{if } n = 2p + 1 \end{cases} \quad (4.7)$$

The approximation coefficients a_{j+1} and detail coefficients d_{j+1} are calculated through convolution operations (denoted by the symbol $\star$) between the approximation coefficients from the previous level a_j and the respective filters:

$$a_{j+1}[p] = \sum_{n=-\infty}^{+\infty} h[n-2p]a_j[n] = a_j \star \bar{h}[2p], \quad (4.8)$$

$$d_{j+1}[p] = \sum_{n=-\infty}^{+\infty} g[n-2p]a_j[n] = a_j \star \bar{g}[2p]. \quad (4.9)$$

The filter coefficients are derived from inner products (denoted by $\langle \cdot, \cdot \rangle$) of the scaling and wavelet functions:

$$h[n-2p] = \langle \phi_{j+1,p}, \phi_{j,n} \rangle \quad (4.10)$$

$$g[n-2p] = \langle \psi_{j+1,p}, \phi_{j,n} \rangle \quad (4.11)$$

At each decomposition level j , the detail coefficients d_j capture frequency components in the range $[2^{-(j+1)}, 2^{-j}]$ of the normalized frequency, while the approximation coefficients a_j contain the remaining lower frequencies. This cascading filter process progressively separates high-frequency components from the original signal, while preserving lower frequencies in the approximation coefficients. The orthonormal bases ensure energy preservation at every decomposition level, enabling perfect reconstruction of the original signal. The reconstruction process can be expressed using the downsampling operation from Eq. (4.7):

$$\begin{aligned} a_j[p] &= \sum_{n=-\infty}^{+\infty} h[p-2n]a_{j+1}[n] + \sum_{n=-\infty}^{+\infty} g[p-2n]d_{j+1}[n] \\ &= \check{a}_{j+1} \star h[p] + \check{d}_{j+1} \star g[p] \end{aligned} \quad (4.12)$$

Through successive filtering operations, the low-frequency component $\check{a}_{j+1} \star h[p]$ represents the signal's *trend*. Using the reconstructed signals, the original signal can be perfectly reconstructed through a multi-resolution decomposition:

$$A_0 = A_j + \sum_{i=1}^j D_i \quad (4.13)$$

where A_0 represents the original signal, A_j denotes the reconstructed approximation at level j (trend component), and D_i represents the reconstructed detail signal at level i ($i = 1, 2, \dots, j$). This multi-resolution decomposition allows us to analyze the signal at different time scales while maintaining the ability to perfectly reconstruct the original signal.

b. Application to dataset

The Discrete Wavelet Transform (DWT) method is employed in this study to identify shoreline trends and analyze variance across different time scales. This approach has been successfully applied in analyzing hydrological time series data, notably in separating

Table 4.4 DWT decomposition levels and corresponding time scales

Level	Frequency Band	Time Scale (month)
1	D_1	2–4
2	D_2	4–8
3	D_3	8–16
4	D_4	16–32
5	D_5	32–64
6	D_6	64–128
7	D_7	128–256
8	D_8	256–512
8	A_8	>512

trend, periodicity, and noise components from an 89-year monthly average temperature dataset (Sang et al., 2013). However, Sang et al. (2013) identified three critical factors that influence trend identification accuracy:

- Selection of wavelet function
- Choice of decomposition level
- Signal-to-noise ratio (SNR)

Their research demonstrated that higher SNR values significantly improve trend identification accuracy. Based on these findings, our study analyzes Hasaki beach shoreline data from 1986 to 2021, using monthly averages (Figure 4.7 (a)). This averaging process serves dual purposes: it inherently smooths out high-frequency variations such as daily and weekly fluctuations, while also creating uniformly sampled time series data required for discrete wavelet transform analysis. The analysis employs three conventional wavelets: Daubechies-6 (db6), Symlets-6 (sym6), and Biorthogonal-3.9 (bior3.9). The maximum decomposition level is set to $\log_2 N = 8$, where N represents the data length, as this allows us to examine temporal scales up to the full length of the dataset.

Using the bior3.9 wavelet, we performed signal reconstruction at multiple decomposition levels (shown in Figure 4.12). This wavelet choice provided better-fitted trends at higher decomposition levels compared to sym6 and db6 wavelets (results shown in Figures A.2 and A.1 in Appendix A).

The level 5 approximation signal (A_5) effectively captured long-term variations (trends) with time scales exceeding 64 months (5.3 years), as indicated in Table 4.4. It is important to note that the reconstructed detail signal (D_j) at level j represents the signal's projection amplitude in the corresponding vector space, rather than actual signal components.

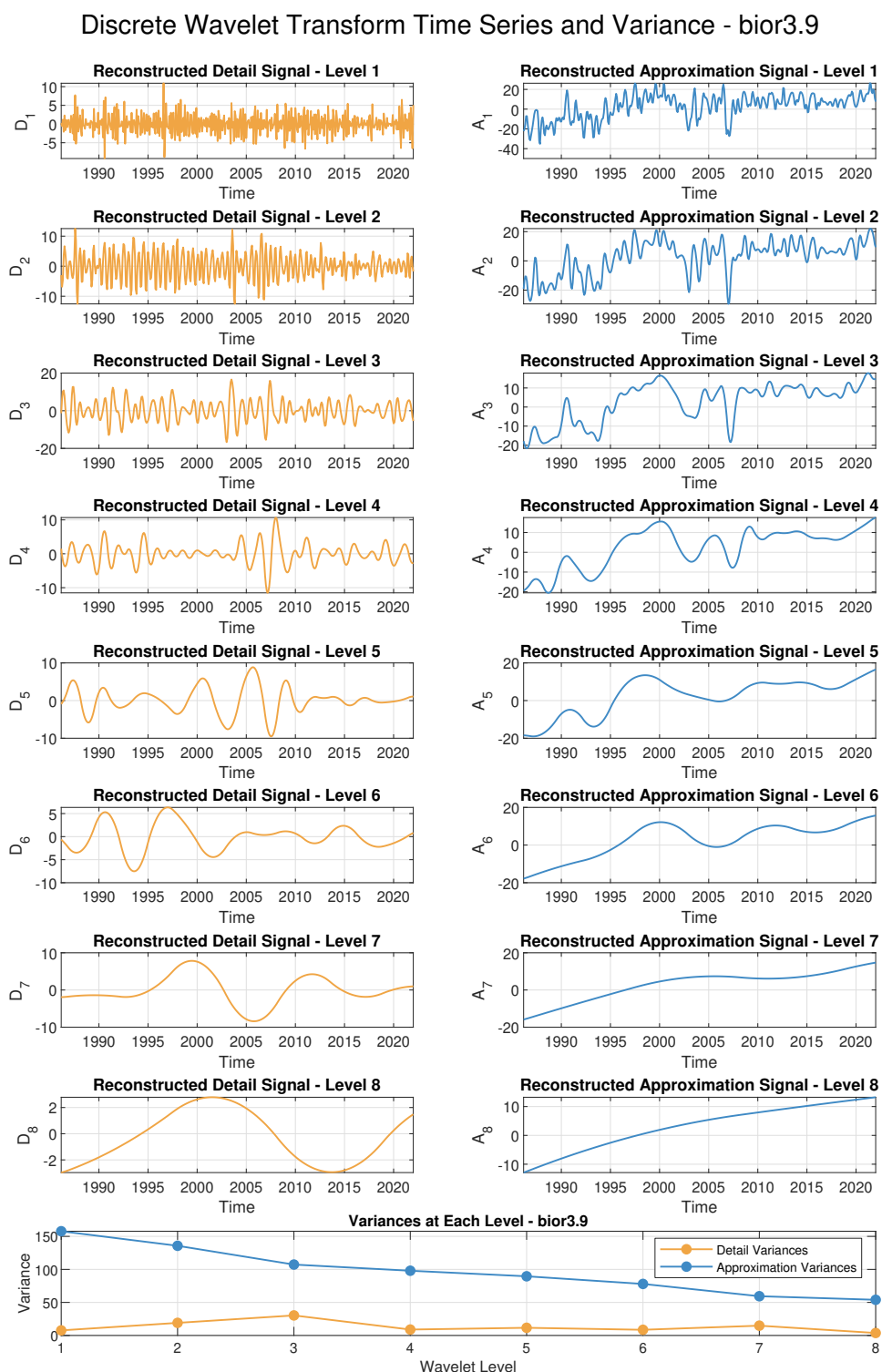


Fig. 4.12 Discrete Wavelet Transform decomposition of monthly averaged shoreline position using **bior3.9** wavelet. Reconstructed detail signal (D_1 - D_8 , left), reconstructed approximation signal (A_1 - A_8 , right), and their respective variances (bottom) at each decomposition level.

To identify dominant components, we evaluated the energy distribution by calculating the variance of D_j at each level. As shown in Figure 4.12, levels 2 and 3 exhibited relatively higher energy, corresponding to time scales of 4-8 months and 8-16 months, respectively. These time scales align with biannual and annual components, explaining the seasonal shoreline behaviors illustrated in Figure 3.4.

Long-term variations are typically attributed to longshore sediment transport, while annual and seasonal variations are normally associated with wave-induced changes. The A_5 signal revealed approximately 30-meter long-term variations over the entire period. We compared this DWT-based trend identification with a conventional 5-year moving window average method. Figure 4.13(a) demonstrates that the DWT approach better captured specific events, such as the 1991 erosion and subsequent accretion until 1994, due to its superior time-frequency localization capabilities. While both methods showed similar performance in identifying trends after 2007 when long-term variations stabilized, DWT demonstrated sharper frequency band separation and reduced inter-band leakage, making it more effective at preserving long-term trends compared to the sliding window approach.

4.3.2 Temporal patterns and variability

Following the analysis in the previous section, we used moving window and DWT methods to filter out long-term trends (longer than 5 years) from the monthly averaged data. The resulting detrended signals in Figure 4.13(b)(c) reveal clear periodic variations. In this section, we investigate these variations and their relationship with wave conditions through cross-spectral analysis.

The Cross Power Spectral Density (CPSD) analysis quantifies how two time series are related at different frequencies. The magnitude of CPSD indicates the strength of correlation between two signals at each frequency, while the phase difference reveals their temporal relationship. Our analysis reveals two statistically significant peaks in the magnitude spectrum (Figure 4.14(a)), corresponding to annual (0.99 years, $f \approx 0.083$ cycles/month) and semi-annual (0.50 years, $f \approx 0.167$ cycles/month) cycles. These peaks indicate strong correlations between wave height and shoreline position at these specific frequencies, suggesting that both annual and semi-annual wave patterns significantly influence shoreline behavior.

The annual cycle shows the strongest correlation with shoreline position, reflecting the importance of seasonal wave patterns. The semi-annual peak may be attributed to the increased frequency of explosive extratropical cyclones around March, which typically generate high-energy wave conditions.

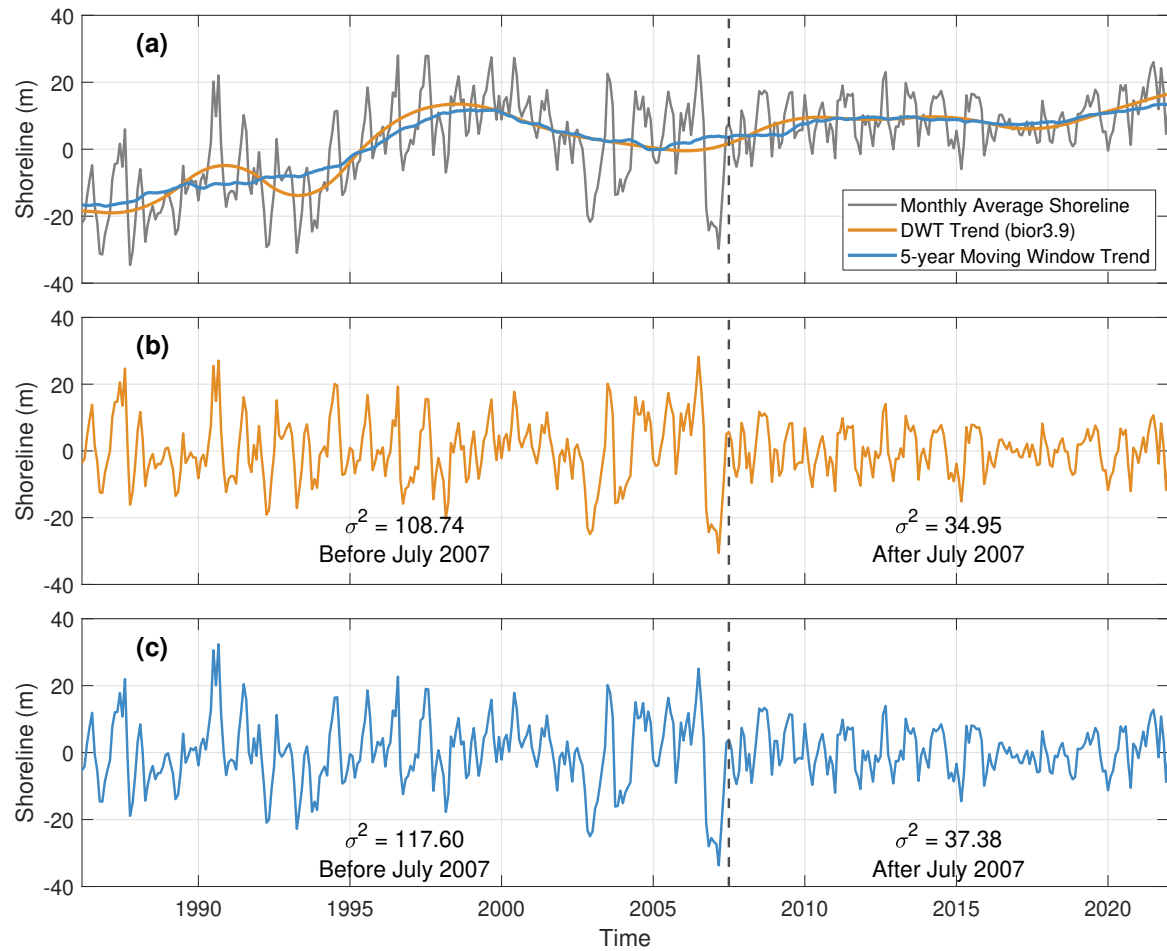


Fig. 4.13 Comparison of trend extraction methods and shoreline variability analysis: (a) Monthly averaged shoreline position with trends extracted using DWT (bior3.9 wavelet) and 5-year moving window methods; (b) Detrended shoreline fluctuations using DWT method; (c) Detrended shoreline fluctuations using 5-year moving window method.

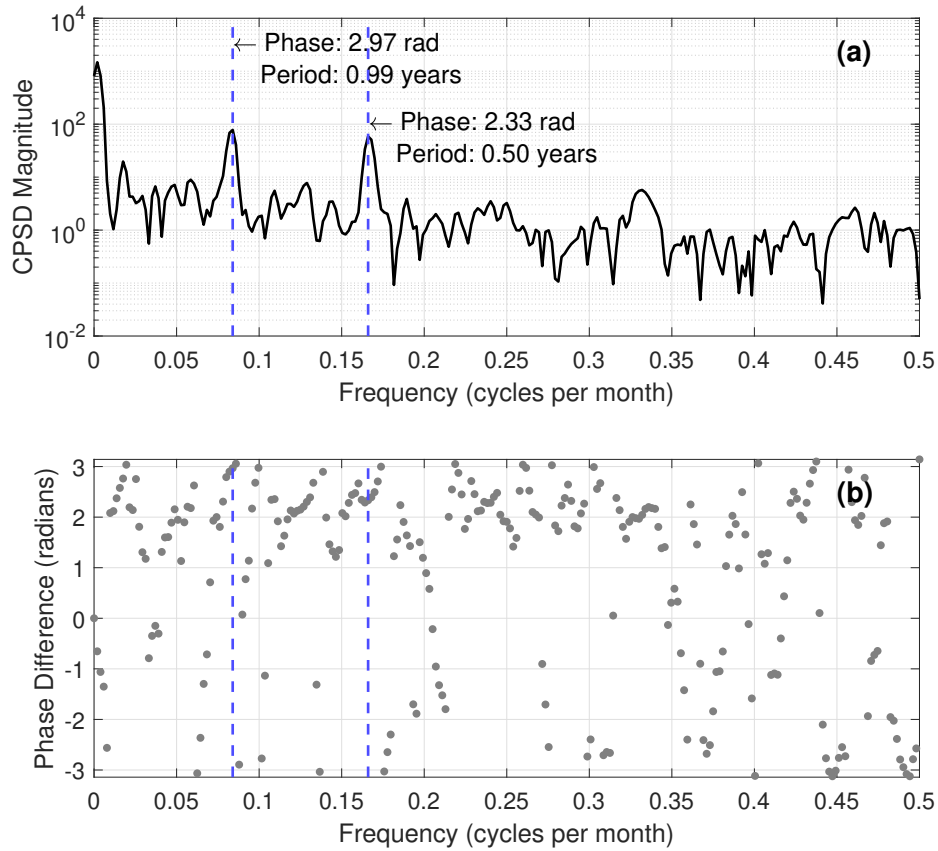


Fig. 4.14 Cross Power Spectral Density (CPSD) analysis between monthly averaged wave height and shoreline position. (a) CPSD magnitude spectrum; (b) Phase difference.

Phase analysis (Figure 4.14(b)) provides further insight into the temporal dynamics between wave forcing and shoreline response. At both identified frequencies, the phase differences approach π radians (2.97 and 2.33 rad for annual and semi-annual cycles, respectively). This phase difference of approximately π radians indicates a negative correlation, where any increase in wave height corresponds to a decrease in shoreline position (retreat), while periods of small waves correlate with shoreline advance. Such behavior aligns with established understanding of cross-shore sediment transport processes, where energetic waves typically promote offshore sediment movement and beach erosion.

This spectral analysis demonstrates that wave conditions play a significant role in driving shoreline variations through a phase-lagged relationship, with both annual cycles and storm-induced changes contributing to the observed shoreline dynamics. It is worth noting that the amplitude of these variations shows a significant decrease after July 2007, as evident in both the detrended signals and wavelet detail components D_2 and D_3 (Figure 4.13(b)(c)). The underlying cause of this reduction requires further investigation.

Chapter 5

Wave-calibrated shoreline equilibrium model and the performance

5.1 Outline of equilibrium model

As introduced in Chapter 2, among the conventional reduced complexity models for cross-shore sediment transport, both Y09 (Yates et al., 2009) and ShoreFor (Davidson et al., 2013) have demonstrated good performance at open and semi-embayyed beaches worldwide. The wave-driven equilibrium shoreline model, ShoreFor, was selected for this study due to its explicit incorporation of wave climate in defining equilibrium conditions, unlike Y09 which defines equilibrium through shoreline position. This distinction makes ShoreFor particularly suitable for exploring the intrinsic relationship between model parameters and wave climate. The model has proven effective in reproducing shoreline variability at exposed sandy beaches where cross-shore sediment transport processes are dominant, conditions similar to those at Hasaki Beach. Furthermore, Splinter et al. (2014) evaluated the model's capability to simulate shoreline morphodynamic changes using high water level references across global beaches, noting its efficiency with short computation times. This makes ShoreFor particularly suitable for mid- to long-term simulations in our study. Thus, following the equilibrium model proposed by Davidson et al. (2013), the change in shoreline position is related to disequilibrium and wave energy flux as follows:

$$\frac{dY}{dt} = \begin{cases} C^a \cdot F^+ + b, & \text{if } \Delta\Phi \geq 0 \\ C^e \cdot F^- + b, & \text{if } \Delta\Phi < 0 \end{cases} \quad (5.1)$$

$$F = P^{0.5} \frac{\Delta\Phi}{\sigma_{\Delta\Phi}} \quad (5.2)$$

$$\Delta\Phi = \Phi_{eq} - \Phi \quad (5.3)$$

where Y is the shoreline position, C^a and C^e are the accretion and erosion efficiency coefficients ($m^{1.5}s^{-1}W^{-0.5}$), F is the forcing term, b is a linear term (m/s), and $\sigma_{\Delta\Phi}$ is the standard deviation of the disequilibrium $\Delta\Phi$. The disequilibrium is determined by the difference between the equilibrium state Φ_{eq} and the time-varying wave-forcing variant Φ , which can be represented by three widely used parameters:

$$\Phi = \begin{cases} \Omega = H_s / w T_p & \propto H_s T_p^{-1} \\ H_s & \propto H_s T_p^0 \\ P = EC_g & \propto H_s^2 T_p^1 \end{cases} \quad (5.4)$$

where Ω is the dimensionless settling velocity, H_s is the significant wave height (m), P is the wave power (Watts), T_p is the peak wave period (s), w is the settling velocity of on-site sediment (m/s), $E = 1/16\rho g H_s^2$ is the significant wave energy (N/m), and C_g is the wave group velocity (m/s).

The equilibrium state is calculated as a weighted average of past wave conditions:

$$\Phi_{eq} = \left[\sum_{i=1}^{2\phi} 10^{-i/\phi} \right]^{-1} \sum_{i=1}^{2\phi} \Phi_i 10^{-i/\phi} \quad (5.5)$$

where ϕ is the response factor (day) and i represents the number of days prior to the present time. According to this equation, the weight of past wave conditions decays exponentially over time, with more recent conditions having greater influence on the equilibrium state. A positive $\Delta\Phi$ indicates shoreline restoration, while a negative value indicates erosion.

The efficiency coefficients C^a and C^e , traditionally assumed to be time-invariant and site-specific, control the sensitivity of the shoreline to wave disequilibrium. In this study, these parameters are treated as non-stationary and their relationship with wave conditions will be investigated in the subsequent sections.

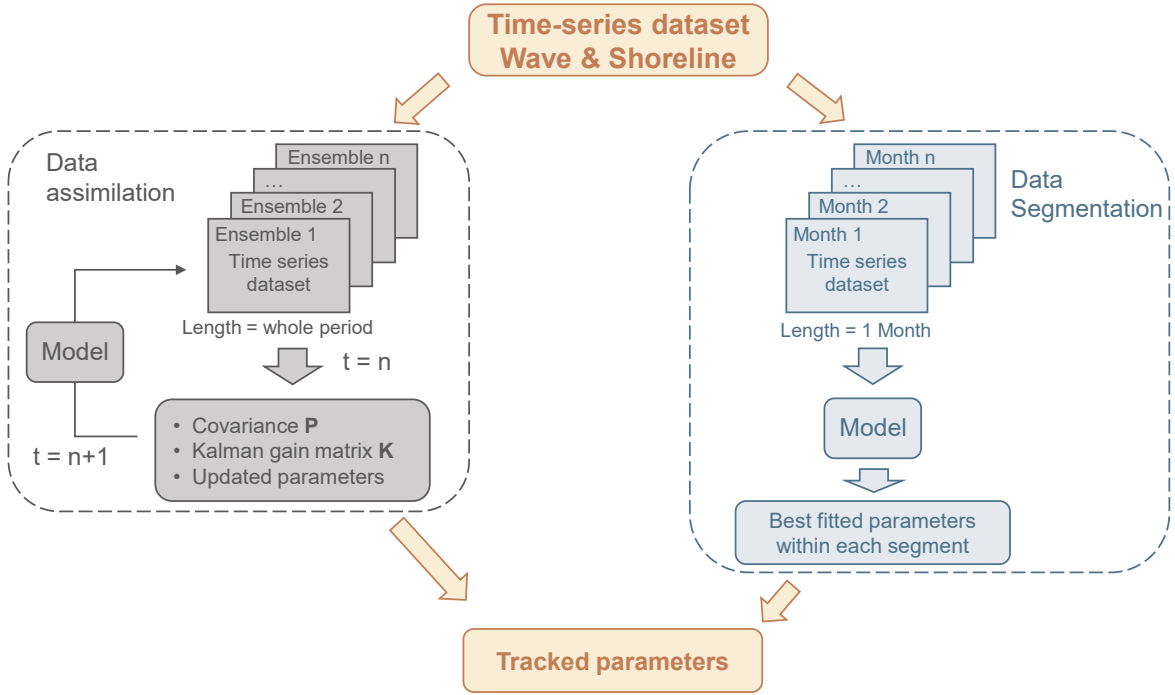


Fig. 5.1 Overview of data assimilation and data segmentation in tracking parameters

5.2 Non-stationary parameter optimization

To explore the non-stationarity of free parameters in ShoreFor, we employed two distinct methods: a novel approach based on data segmentation, outlined in Section 5.2.1, and data assimilation using the Ensemble Kalman Filter (EnKF), described in Section 5.2.2. Figure 5.1 provides an overview of these two methodologies, illustrating their key differences and complementary nature.

The data segmentation approach divides the time-series dataset into independent segments, fitting the model separately within each segment, which makes it ideal for detecting localized variations without the dependence on preceding states. In contrast, EnKF incorporates data assimilation by iteratively updating model states with observational data. It allows parameters to evolve over time by relying on the previous model state, thus effectively capturing the temporal dynamics of the system.

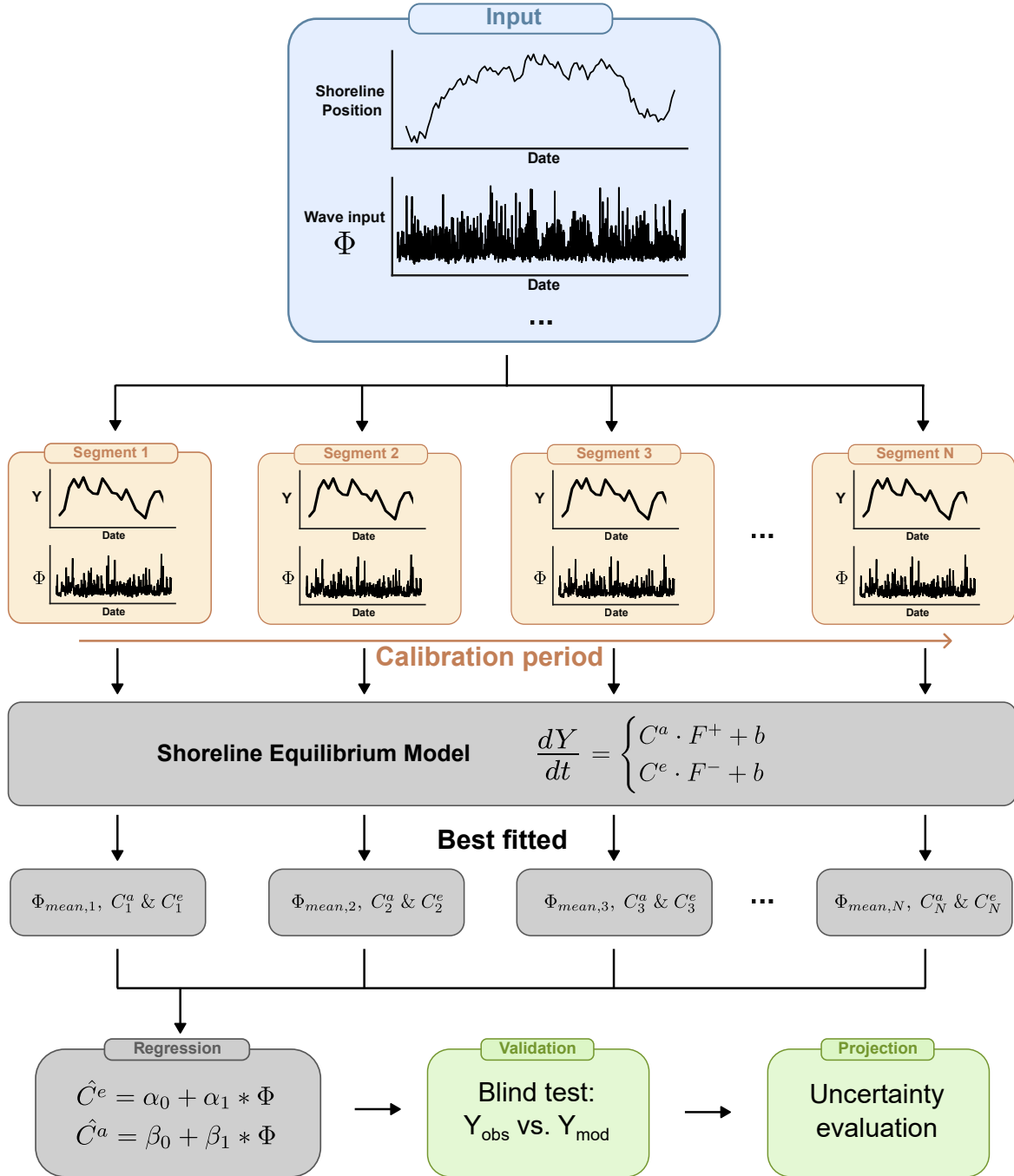


Fig. 5.2 Flowchart of the segmentation-based non-stationary parameter approach.

5.2.1 Data segmentation

a. Theoretical framework

To investigate the temporal variability of shoreline response sensitivity, we develop a segmentation and regression approach that allows the efficiency coefficients to vary with wave conditions (Figure 5.2).

Initially, the ShoreFor model with stationary parameters is applied to the entire calibration period to determine the optimal response factor, denoted as ϕ^* (where the asterisk indicates the optimal value). This optimal value is obtained by minimizing the root mean square error between the modeled and observed shoreline positions. The optimized ϕ^* value is then used to calculate the disequilibrium term throughout the subsequent analysis.

The approach then proceeds in three main steps. First, the calibration period is divided into segments, with the segment length determined by two key considerations: ensuring sufficient data points within each segment for reliable parameter estimation, and capturing distinctly different wave conditions between segments. The segment length should be long enough to contain adequate data for stable parameter estimation but short enough to resolve temporal variations in wave forcing. For each segment, the ShoreFor model is applied to obtain the best-fit shoreline change efficiency coefficients C^a and C^e through error minimization.

Second, linear regression relationships are established between these coefficients and the period-average wave-forcing variant:

$$\begin{aligned}\hat{C}^e &= \alpha_0 + \alpha_1 \Phi_{mean} \\ \hat{C}^a &= \beta_0 + \beta_1 \Phi_{mean}\end{aligned}\tag{5.6}$$

To ensure the quality of the regression relationships, segments with poor model performance (Normalized Mean Square Error > 0.6) are excluded from the analysis:

$$NMSE = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}\tag{5.7}$$

Finally, these regression relationships are used to predict the non-stationary parameters during the validation period based on the observed wave conditions. The linear trend is subtracted from both modeled and observed shoreline positions, which generally represents longshore transport. While this trend could partially result from wave-induced residual changes, its magnitude is relatively small (one order of magnitude smaller) com-

pared to the seasonal variations in shoreline position. As this study focuses primarily on wave-induced seasonal variations, removing the trend enables a more direct comparison of the model's ability to capture these seasonal patterns.

b. Application to dataset

The methodology is tested using shoreline data from Hasaki Beach spanning from 1991 to 2015. Based on the daily shoreline sampling frequency during 1991-2010 and the distinct seasonal cycle in wave conditions at Hasaki Beach, a one-month segment length is adopted for the analysis. This choice ensures sufficient data points within each segment while capturing the seasonal variations in wave forcing.

Two distinct experimental approaches are employed to evaluate the model's performance with non-stationary parameters. First, a moving window analysis is conducted to assess the model's short-term behavior from 1991 to 2010. This involves using a 5-year calibration period followed by a 2-year validation period, with the window advancing by one year at each step. This approach enables evaluation of the model's performance under varying wave conditions and shoreline states over shorter time frames.

Second, a hindcast analysis is performed for the period 1998-2008, during which the shoreline exhibits distinct variability patterns before and after 2003. This period is particularly suitable for examining the capability of wave-calibrated parameters to capture changing shoreline behavior, as the shoreline shows notably increased variability after 2003. Both stationary and non-stationary models are applied to this period to evaluate their ability to reproduce these observed changes in shoreline dynamics.

Third, a long-term analysis is performed using a 20-year calibration period (1991-2010) and a 5-year validation period (2011-2015). For comparison, the original ShoreFor model with stationary parameters is recalibrated using the same calibration period. Model performance is evaluated using both root mean square error (RMSE) and correlation coefficient (R), which provide a comprehensive assessment of both prediction accuracy and pattern reproduction:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (5.8)$$

To assess the uncertainty in model predictions, we employ the widely-used bootstrap method (Efron, 1979), performing 1000 ensemble simulations. Each ensemble is generated by randomly sampling (with replacement) from the original segments, and the regression relationships are recalculated. The 95% confidence interval of the modeled shoreline position is determined from the 2.5th and 97.5th percentiles of the ensemble results.

5.2.2 Ensemble Kalman Filter

a. Theoretical framework

The Ensemble Kalman Filter (EnKF) provides a systematic approach to combining numerical model predictions with observational data, while accounting for uncertainties in both the model and measurements. Originally proposed by Evensen (1994), the EnKF has emerged as an efficient data assimilation technique for nonlinear dynamical systems due to its ability to handle model nonlinearity without requiring analytical derivation of Jacobian matrices. The following theoretical framework follows the EnKF formulation described in Vitousek et al. (2021), where it was applied to equilibrium shoreline modeling using Yates' model. While the underlying EnKF methodology remains the same, this study applies it to the ShoreFor model.

The fundamental principle of EnKF lies in its ensemble-based representation of the system state. Let the model state vector be represented as:

$$\boldsymbol{\psi} = [\vec{\psi}_1 \ \vec{\psi}_2 \ \dots \ \vec{\psi}_{N_{\text{ens}}}] \quad (5.9)$$

where each state vector $\vec{\psi}_i$ of the N_{ens} member ensemble contains both the model solution and parameters. The EnKF implements a sequential assimilation procedure through the following steps:

a.1 Forward model propagation

The forward model is run with added noise to account for model uncertainties:

$$\boldsymbol{\psi}^* = \mathbf{F}(\boldsymbol{\psi}^n) + \boldsymbol{\varepsilon} \quad (5.10)$$

where $\boldsymbol{\psi}^*$ represents the forecasted state vector, $\boldsymbol{\psi}^n$ is the model state vector at time step n , $\mathbf{F}$ denotes the forward model operation where the equilibrium model applies, and $\boldsymbol{\varepsilon} \sim \mathcal{N}(0, \sigma^2)$ represents random additive noise drawn from a normal distribution. This stochastic approach ensures proper representation of model uncertainties in the forecasting step.

a.2 Ensemble covariance calculation

The covariance of the model ensemble is computed as:

$$\mathbf{P} = \text{cov}(\boldsymbol{\psi}^*) = \frac{1}{N_{\text{ens}} - 1} \sum_{i=1}^{N_{\text{ens}}} (\boldsymbol{\psi}_i^* - \bar{\boldsymbol{\psi}}^*)(\boldsymbol{\psi}_i^* - \bar{\boldsymbol{\psi}}^*)^T \quad (5.11)$$

where $\bar{\boldsymbol{\psi}}^*$ represents the ensemble average state vector. This formulation provides a key advantage as it eliminates the need for explicit computation of model Jacobians, significantly reducing computational complexity.

a.3 Kalman gain computation

The Kalman gain $\mathbf{K}$, which determines the optimal weighting between model predictions and observations, is calculated as:

$$\mathbf{K} = \mathbf{P}\mathbf{H}^T(\mathbf{H}\mathbf{P}\mathbf{H}^T + \mathbf{R})^{-1} \quad (5.12)$$

where $\mathbf{H}$ is the observation operator relating model states to observations, and $\mathbf{R}$ represents the covariance matrix of perturbed observations:

$$\mathbf{R} = \frac{1}{N_{\text{ens}} - 1} \sum_{i=1}^{N_{\text{ens}}} (\boldsymbol{\epsilon}_{\text{obs}})_i (\boldsymbol{\epsilon}_{\text{obs}})_i^T \quad (5.13)$$

with $\boldsymbol{\epsilon}_{\text{obs}} \sim \mathcal{N}(0, \sigma_{\text{obs}}^2)$ representing observation noise drawn from a normal distribution with variance σ_{obs}^2 .

a.4 State vector update

The final analysis step updates the state vector according to:

$$\boldsymbol{\psi}^{n+1} = \boldsymbol{\psi}^* + \mathbf{K}([\boldsymbol{\psi}_{\text{obs}}^{n+1} + \boldsymbol{\epsilon}_{\text{obs}}] - \mathbf{H}\boldsymbol{\psi}^*) \quad (5.14)$$

where $\boldsymbol{\psi}^{n+1}$ represents the final (analysis) state vector. The bracketed term represents the innovation - the difference between perturbed observations and model predictions - which is scaled by the Kalman gain $\mathbf{K}$ to update the state vector appropriately.

In the absence of observations, the state vector is simply predicted by the forward model ($\boldsymbol{\psi}^{n+1} = \boldsymbol{\psi}^*$). While the method requires running an ensemble of model realizations, its ability to handle nonlinear systems and efficient treatment of uncertainties makes it particularly suitable for complex dynamical systems.

b. Application to dataset

b.1 Data preprocessing and model setup

The shoreline dataset spans from 1991 to 2010 with daily measurements at Hasaki beach. To filter out high-frequency variations that could disturb the assimilation process, the data is averaged over 7-day windows. The plumb line measurement uncertainty at Hasaki beach is approximately 1 meter, which defines our observation error covariance matrix $\mathbf{R}$ (Eq. (5.13)).

Prior to implementing the EnKF, the optimal response factor ϕ is calibrated using the entire dataset by minimizing the model error. This calibrated ϕ value remains constant throughout the assimilation period. Following previous studies (Ibaceta et al., 2022), the dimensionless settling velocity Ω is chosen as the forcing variant to facilitate comparison with existing literature.

b.2 EnKF implementation

The ShoreFor model is integrated within the EnKF framework to simulate shoreline evolution while continuously updating its free parameters. The state vector combines both the modeled shoreline position and the free parameters:

$$\vec{\psi} = [Y \quad C^a \quad C^e]^T \quad (5.15)$$

where Y represents the shoreline position, and C^a and C^e are the shoreline response parameters to wave conditions. The observation operator $\mathbf{H}$ maps the model state to the observable quantity (shoreline position):

$$\mathbf{H} = [1 \quad 0 \quad 0]^T \quad (5.16)$$

b.3 Model integration and ensemble management

In the forward propagation step (Eq. (5.10)), each ensemble member's state evolves according to the ShoreFor model equation (Eq. (5.1)). The assimilation occurs at each time step where shoreline observations are available, allowing continuous updating of the efficiency coefficients C^a and C^e throughout the study period. After each assimilation step, the state vector ψ is recorded, providing a temporal evolution of shoreline position and the free parameters $C^a(t)$ and $C^e(t)$. This time series of parameters reveals how the beach response characteristics vary throughout the study period.

To prevent filter divergence and maintain ensemble spread, an inflation step is applied after each Kalman update (Eq. (5.14)):

$$\boldsymbol{\psi}_{\text{inflated}}^{n+1} = \bar{\boldsymbol{\psi}}^{n+1} + \boldsymbol{\lambda} \odot (\boldsymbol{\psi}^{n+1} - \bar{\boldsymbol{\psi}}^{n+1}) \quad (5.17)$$

where $\bar{\boldsymbol{\psi}}$ is the ensemble mean state vector, $\boldsymbol{\lambda}$ is the inflation factor vector $[1, 1.01, 1.01]^T$ for shoreline position and free parameters (C^a and C^e) respectively, and $\odot$ denotes element-wise multiplication. This inflation step slightly increases the deviation of the free parameters from their ensemble means, helping to maintain sufficient ensemble spread and prevent premature convergence of the parameter estimates. The inflated state vector $\boldsymbol{\psi}_{\text{inflated}}^{n+1}$ is then used as the initial condition for the forward propagation in the next time step, ensuring the maintained ensemble spread carries forward in the assimilation cycle.

5.3 Model results

5.3.1 Non-stationary parameters

a. Segmentation

The model calibration reveals several key parameters that characterize shoreline response to wave forcing at Hasaki Beach. During the calibration period, the 20-year shoreline and wave time series data is divided into 240 segments (12 months $\times$ 20 years) for regression analysis. After applying the NMSE threshold, 194 segments remain. Significant wave height (H_s) is used as wave-forcing variant to illustrate the relationships with model parameters in the following analysis, while similar analyses using dimensionless settling velocity (Ω) and wave energy (P) are shown in Appendix B.

The model with non-stationary and stationary parameters shares the same response factor (ϕ) and equilibrium state ($H_{s,eq}$), indicating they are designed to reflect the same accretion/erosion responses to wave conditions. The optimized response factor (ϕ) at Hasaki Beach is 100, indicating a relatively short memory of past beach state conditions. Although Hasaki is an open coast, its ϕ value is similar to that of Narrabeen-Collaroy Beach, an embayed beach, and one order of magnitude lower than other open coasts like Truc Vert (Splinter et al., 2014).

Figure 5.3 shows the temporal evolution of C^a and C^e with H_s , where higher values of C^a typically occur during high-wave periods, while extreme high values of C^e are usually found during low-wave periods. To further explore the relationship between wave conditions and free parameters, Figure 5.4 illustrates the relationships between monthly-

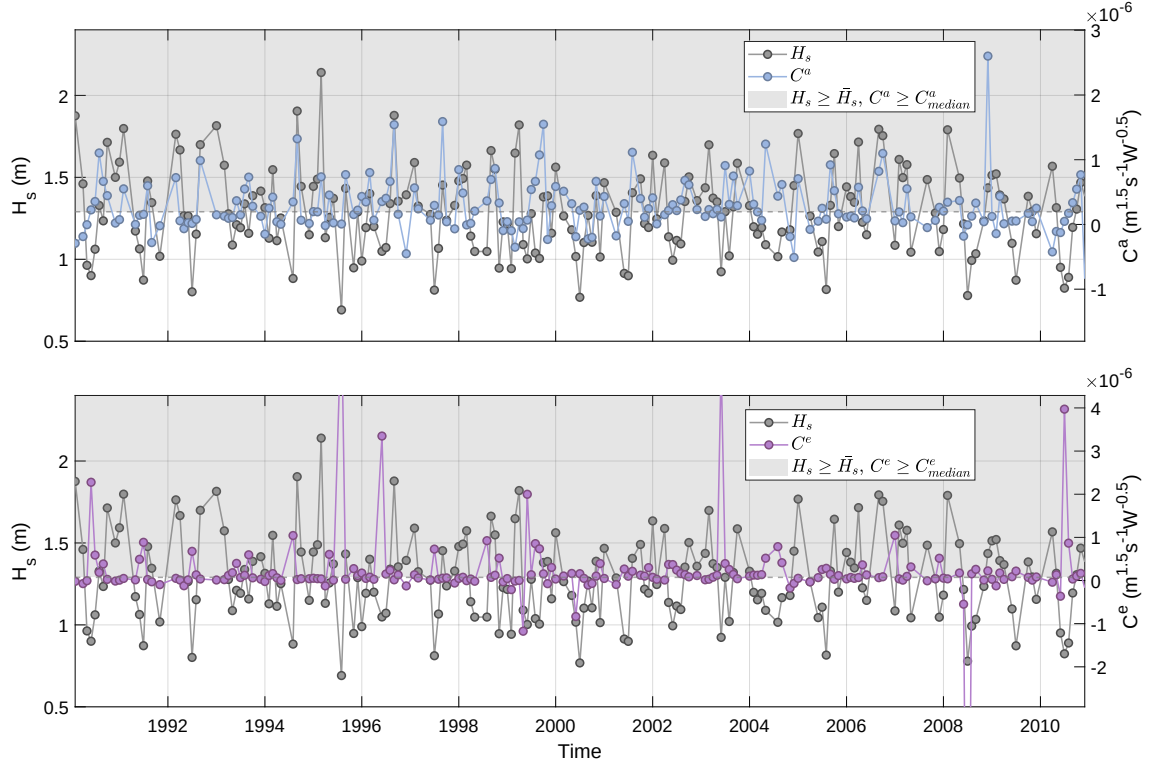


Fig. 5.3 Time series data of H_s with C^a and C^e in the whole calibration period, each scatter represents one segment and the grey shaded area represents $H_s \geq \bar{H}_s$ or $C \geq C_{median}$

averaged significant wave height (H_s) and both erosion (C^e) and accretion (C^a) efficiency coefficients, including their distribution patterns relative to mean wave height. Each scatter point represents a segment from the calibration period. For C^e , the data converge to a constant value as wave height increases, indicating no significant correlation with H_s , especially for wave heights greater than the mean of 1.29 m. The optimal stationary value C^{e*} calculated from the calibration period is slightly lower than the median segment value $\tilde{C}^e$ but remains within the same order of magnitude. The peak value of C^e does not vary significantly with H_s , supporting the use of a constant value for C^e .

In contrast, the relationship between C^a and H_s is more scattered, though a statistically significant ($p=0.003$) weak positive correlation is observed. This suggests that higher wave heights are associated with higher accretion efficiency. Unlike C^e , C^a shows increased variability with H_s , and the probability density plot indicates that the peak of the C^a distribution shifts to higher values as H_s exceeds the mean. Consequently, segments with higher wave heights are more likely to have higher C^a values.

Therefore, during the validation period, the coefficients C^a and C^e are computed using the regression equations (Eq. (5.6)) with $\alpha_0 = \tilde{C}^e$ and $\alpha_1 = 0$:

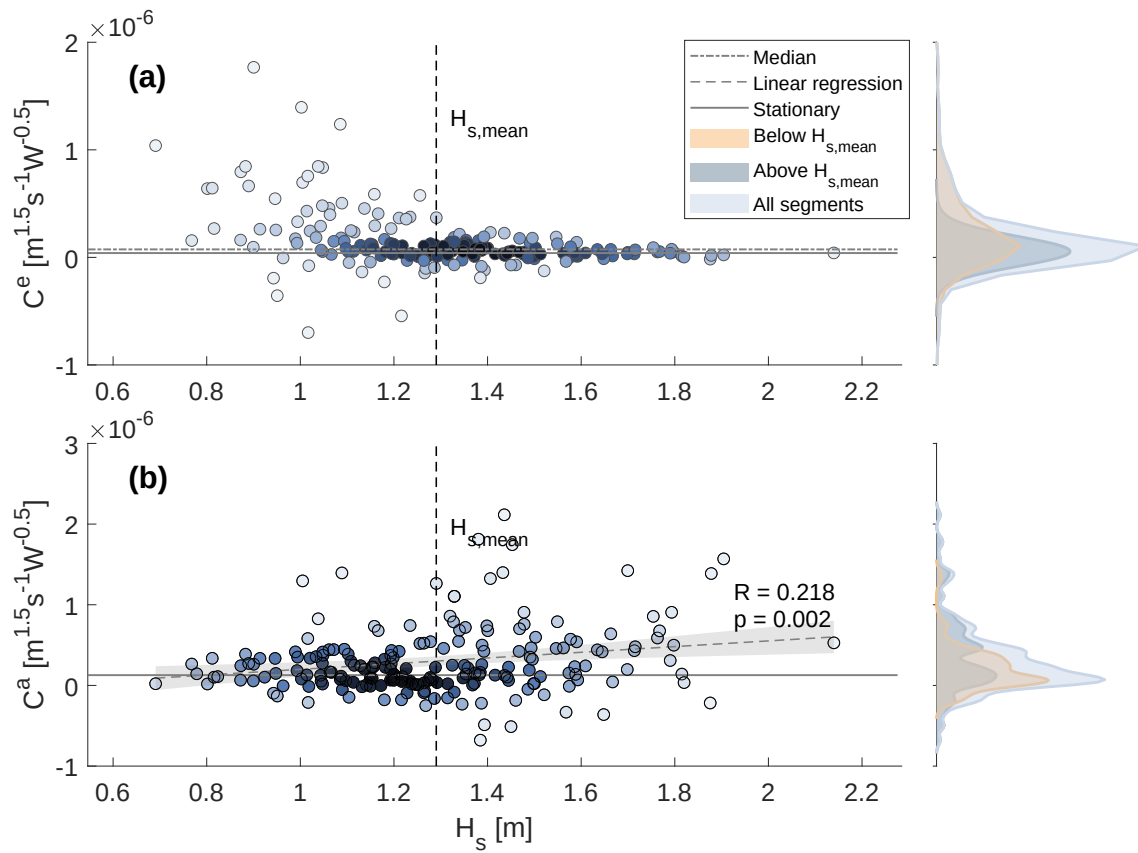


Fig. 5.4 Scatter plots showing the relationship between the variables. (a) H_s and C^e , and (b) H_s and C^a . Both plots include density plots on the right-hand side, showing the distribution of C^e and C^a values above and below mean wave height $H_{s,mean}$. The color of the dots indicates the distribution density of the data points, and the grey shadow area indicates the 95% confidence interval of the regression line.

Table 5.1 Calibrated model parameters for different forcing variants using segmentation

	Non-stationary			Stationary		
	H_s	Ω	P	H_s	Ω	P
ϕ	100	100	100	100	100	100
C^a				1.3×10^{-7}	1.0×10^{-7}	3.1×10^{-9}
C^e				4.0×10^{-8}	4.3×10^{-8}	9.7×10^{-10}
β_1	3.5×10^{-7}	4.6×10^{-7}	3.3×10^{-10}			
β_0	-1.5×10^{-7}	-2.7×10^{-7}	3.7×10^{-9}			
$\tilde{C}^e$	7.4×10^{-8}	1.0×10^{-7}	2.6×10^{-9}			

$$\begin{aligned}\hat{C}^e &= \tilde{C}^e \\ \hat{C}^a &= \beta_1 \cdot H_s + \beta_0\end{aligned}\tag{5.18}$$

The parameters of stationary and non-stationary ShoreFor model with three forcing variants are shown in Table 5.1. Through segmentation analysis of the dataset, the efficiency coefficients exhibit notable variability, particularly in the accretion coefficient C^a , which demonstrates a weak but significant positive correlation with wave forcing.

b. Ensemble Kalman Filter Analysis

To evaluate an alternative approach for tracking parameter variability, we implemented an Ensemble Kalman Filter (EnKF) method. The EnKF tracks free parameters through their covariance matrix P , which is calculated from ensemble members. To mitigate initial parameter instability, we established a two-year “cold start” transition period before tracking parameters from 1991 to 2010, matching the segmentation method’s timeframe.

Figure 5.5(a) shows the temporal evolution of C^a and C^e using EnKF, while Figures 5.5(b,c) illustrate their relationships with significant wave height (H_s). To facilitate comparison with the segmentation approach, we averaged both parameters and wave heights monthly, with each data point representing a monthly mean value. The EnKF method revealed notably different parameter behavior compared to the segmentation approach. While segmentation showed clear correlations between parameters and wave conditions, the EnKF-derived parameters exhibited distinct characteristics. Large-scale temporal shifts in parameter values (e.g., during 2000-2002) occurred without corresponding changes in wave climate. No significant correlation emerged between the parameters and wave height, and the method showed higher parameter variability and sensitivity to initial conditions. These differences can be attributed to several factors. The high-frequency shoreline dataset (daily measurements) presents both opportunities and challenges. While it provides detailed information about short-term shoreline variations, it requires careful data preprocessing to avoid noise interference and challenges the EnKF’s ability to distinguish between meaningful parameter variations and measurement noise.

The fundamental approaches of EnKF and segmentation differ in important ways. EnKF continuously assimilates observations, making it more sensitive to data quality and preprocessing. In contrast, segmentation utilizes all available data points within each segment without requiring extensive preprocessing. Additionally, EnKF may compensate for unmodeled processes through parameter adjustments, potentially masking true parameter-wave relationships. While applying longer averaging periods could potentially

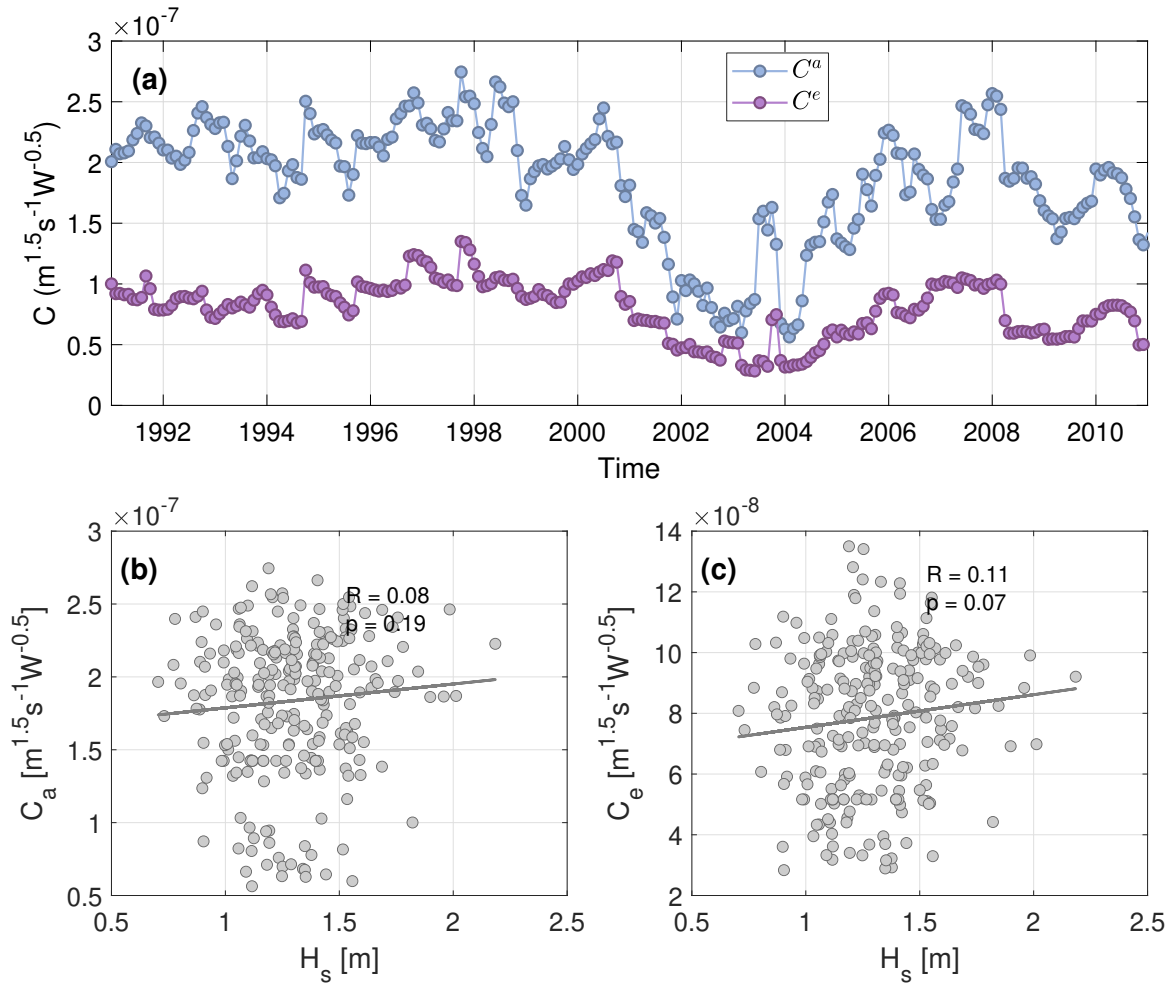


Fig. 5.5 Results of parameter tracking using Ensemble Kalman Filter (EnKF). (a) Time series of accretion efficiency coefficient (C^a) and erosion efficiency coefficient (C^e) from 1991 to 2010; (b,c) Relationship between significant wave height (H_s) and monthly averaged accretion and erosion efficiency coefficients (C^a and C^e), respectively.

reduce noise in the EnKF approach, this would decrease data availability for assimilation, limit the method's ability to capture parameter variability, and reduce its advantages over the segmentation method.

Given these considerations, the segmentation method appears more suitable for this study's objectives. It offers more robust parameter-wave relationship identification, less sensitivity to data preprocessing, better utilization of the available high-frequency measurements, and clearer physical interpretation of parameter variations. These findings suggest that while EnKF remains a powerful tool for data assimilation, the segmentation approach better serves our specific goal of understanding the relationship between wave

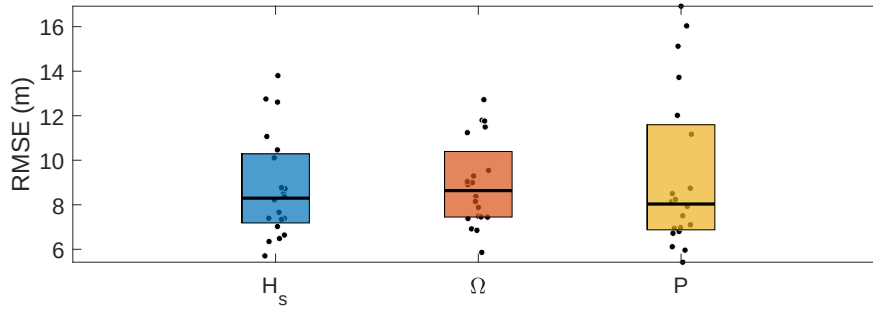


Fig. 5.6 Boxplot of root mean square error (RMSE) of the equilibrium model with different wave-forcing variants in a moving window with a 5-year calibration period followed by a 2-year validation period.

conditions and model parameters. In the subsequent sections, we will focus on discussing the results of the model using the segmentation-calibrated relationships.

5.3.2 Hindcast and validation

a. Short-term Performance Analysis

Prior to conducting long-term hindcast and validation analysis, we evaluated the model's short-term performance using three different wave-forcing variants: significant wave height (H_s), dimensionless settling velocity (Ω), and wave energy (P). This evaluation was particularly important given that our correlation analysis (Figure 4.3) showed that Ω and H_s maintained the strongest and most consistent correlations with shoreline position throughout the year.

Using the moving window approach described in Section 5.2.1, we analyzed model performance across 16 different windows from 1991 to 2010, with each window comprising a 5-year calibration period followed by a 2-year validation period. The Root Mean Square Error (RMSE) was calculated for each variant during the validation periods (Figure 5.6). While all three wave-forcing variants showed similar median RMSE values, they exhibited distinct characteristics in their performance. Wave energy (P) demonstrated the highest variability in performance across different time windows, suggesting less reliable predictive capability. In contrast, significant wave height (H_s) and dimensionless settling velocity (Ω) showed comparable performance ranges between their 25th and 75th percentiles and exhibited more consistent performance across different time windows.

Further analysis revealed important differences in how each variant responded to wave conditions as shown in Figure 5.8. Significant wave height (H_s) showed clear monthly variations (Figure 3.4(b)), which were reflected in its equilibrium state (Figure 5.8(a)).

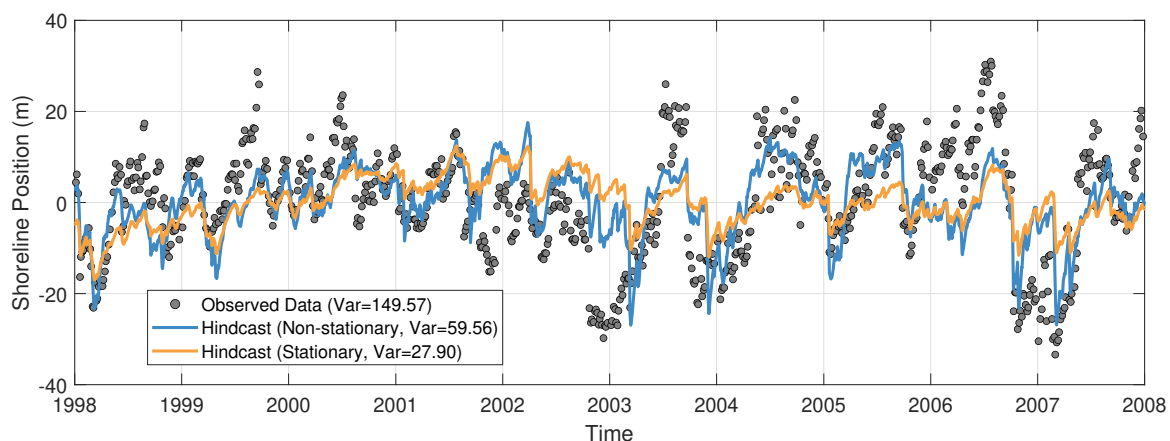


Fig. 5.7 Comparison of shoreline hindcast results from 1998 to 2008 using the ShoreFor model with stationary and non-stationary parameters, with significant wave height (H_s) as the forcing variant

Dimensionless settling velocity (Ω) exhibited the smallest difference between extreme and equilibrium values during high-energy wave conditions, while wave energy (P) showed the largest discrepancy between extreme and equilibrium values, with H_s falling between Ω and P . These differences can be attributed to the mathematical formulation of each variant. Wave energy P varies with the square of significant wave height (H_s^2), while dimensionless settling velocity Ω has an inverse relationship with peak period (T_p). The larger discrepancy observed in wave energy P resulted in greater disequilibrium during erosion events ($\Delta\Phi < 0$) compared to accretion events ($\Delta\Phi > 0$), leading to a less distinct cyclic pattern. Detailed time series of Ω and P variants and their equilibrium states are provided in Appendix B.

This analysis informs our understanding of the relative strengths and limitations of each wave-forcing variant for the subsequent long-term analysis.

Table 5.2 Model hindcast results (1998-2008) for different forcing variants

	Non-stationary			Stationary		
	H_s	Ω	P	H_s	Ω	P
RMSE (m)	9.71	11.07	11.02	11.45	11.49	11.45
R	0.61	0.48	0.55	0.36	0.35	0.36

Table 5.3 Model validation results (2011-2015) for different forcing variants

	Non-stationary			Stationary		
	H_s	Ω	P	H_s	Ω	P
RMSE (m)	8.34	8.77	9.56	7.49	7.26	7.61
R	0.42	0.40	0.35	0.38	0.42	0.33

b. Hindcast

To evaluate the effectiveness of incorporating non-stationary parameters, we compared the hindcast performance of both stationary and non-stationary models over the 10-year period 1998-2008 using significant wave height (H_s) as the forcing variant shown in Figure 5.7. In the non-stationary model, the efficiency coefficients C^a and C^e were calculated using the regression relationships established in Eq. (5.18), with parameters shown in Table 5.1. This allowed the coefficients to vary temporally with wave conditions, in contrast to the fixed coefficients used in the stationary model.

The non-stationary model demonstrated superior performance in reproducing shore-line variability, as evidenced by the performance metrics presented in Table 5.2. Among all three forcing variants, H_s showed the best overall performance. The non-stationary approach with H_s achieved the highest correlation coefficient ($R = 0.61$) and lowest RMSE (9.71 m) compared to both its stationary counterpart and other forcing variants. The non-stationary model successfully reproduced the intensive fluctuation from 2003 to late 2007 which was not captured by the stationary model.

Examining the variance of modeled shoreline positions for H_s provides additional insight into model behavior. The observed shoreline data showed a variance of 149.57 m², while the non-stationary model predicted a variance of 59.56 m² and the stationary model 27.90 m². Although both models underestimated the total variance, the non-stationary approach captured more than twice the variability of the stationary model, suggesting better representation of the dynamic nature of shoreline changes.

c. Validation

Following the hindcast analysis, we evaluated the predictive capabilities of both models using an independent validation period from 2011 to 2015. This validation period serves as a blind test, as these data were not used in the model calibration process. Both stationary and non-stationary models, calibrated using the parameters shown in Table 5.1, were applied to predict shoreline evolution during this period. This validation test is particularly

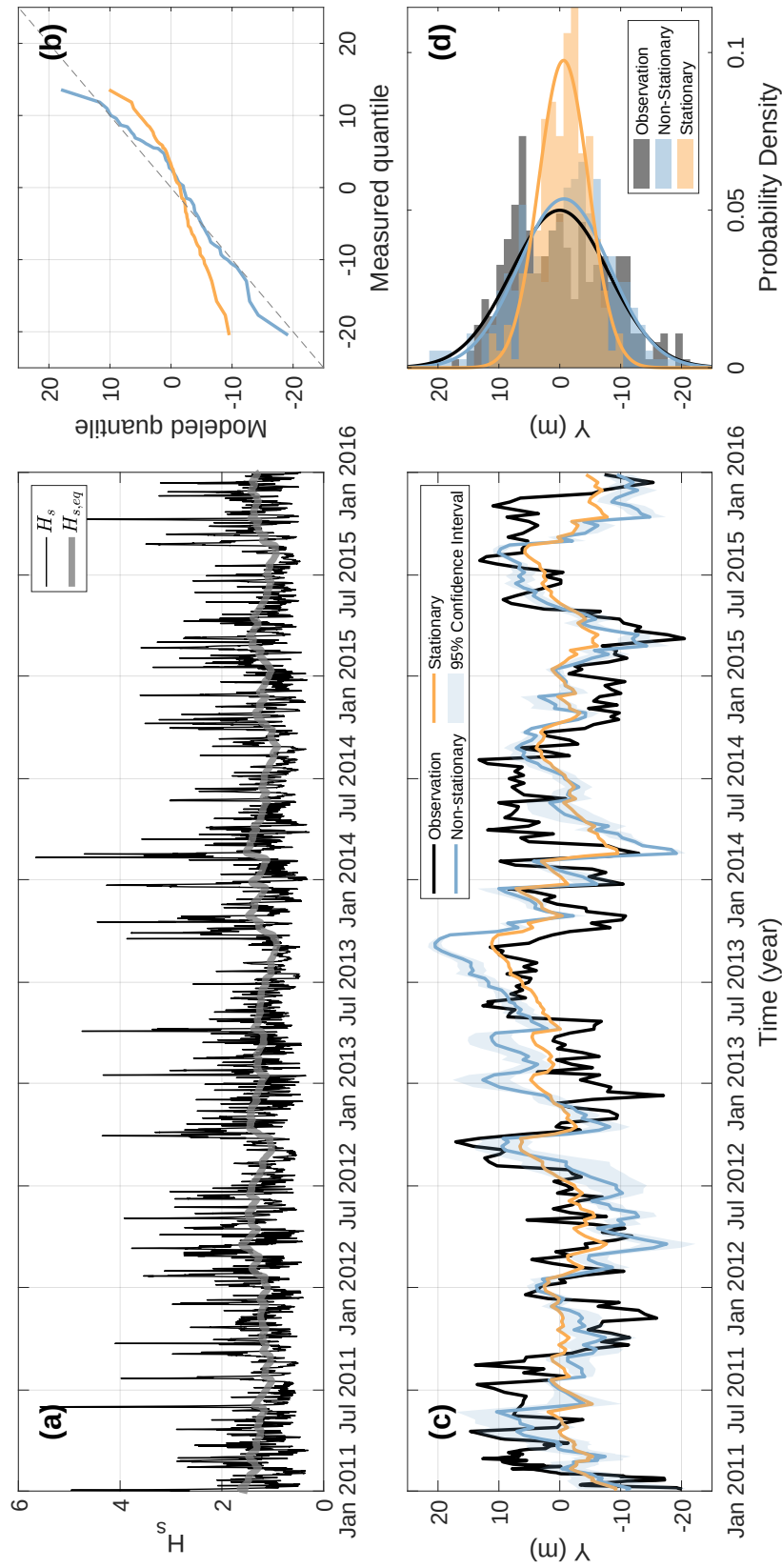


Fig. 5.8 Model validation from 2011 to 2015. (a) Time series of significant wave height H_s and equilibrium significant wave height $H_{s,eq}$; (b) Quantile-quantile plot comparing the model with stationary and non-stationary parameters against the observed shoreline position; (c) Shoreline time series of the model with stationary and non-stationary parameters compared to the observed shoreline position. The shadow area indicates the 95% confidence interval of the model shoreline; (d) Histogram of shoreline positions with the fitted probability density function.

important for assessing the ability of the models to generalize beyond their calibration data and their practical utility for shoreline prediction.

As shown in Table 5.3, when comparing different forcing variants within each model, Ω emerged as the optimal forcing variant ($R = 0.42$, $\text{RMSE} = 7.26$) in the stationary case, consistent with the recommendation of Davidson et al. (2013). For the non-stationary model, H_s showed the best performance ($R = 0.42$, $\text{RMSE} = 8.34$). Notably, in both modeling approaches, P consistently demonstrated the weakest performance with the lowest correlation coefficients and highest RMSE values. Comparing between stationary and non-stationary models, the non-stationary approach exhibited higher RMSE values across all forcing variants, indicating reduced absolute prediction accuracy. However, when using H_s as the forcing variant, the non-stationary model achieved a higher correlation coefficient ($R = 0.42$) compared to its stationary counterpart ($R = 0.38$), suggesting an improved capture of underlying relationships despite lower absolute accuracy. The models differ notably in their ability to capture different types of shoreline changes. The stationary model adequately captures seasonal variations but struggles with extreme events, typically underestimating both erosion and accretion as shown in Figure 5.8. In contrast, the non-stationary model demonstrates superior performance in capturing extreme events, as evidenced by both the quantile-quantile plot (Figure 5.8(b)) and histogram comparisons with observed shoreline positions (Figure 5.8(d)). This is particularly apparent in its accurate reproduction of major accretion events (October 2012, January 2015) and significant erosion periods (January-March 2014, March 2015) (Figure 5.8(c)). However, both models share a common limitation: neither could effectively track shoreline changes during specific periods, notably from late 2012 to mid-2013 and around the end of 2015.

The 95% confidence interval of the model shoreline with non-stationary parameters indicates the shoreline uncertainty induced by the regression parameters (Eq. (5.18)). Consequently, periods with significant uncertainties in the shoreline hindcast often coincide with times when wave height changes rapidly and substantially. For instance, in May 2011 and July 2012, there were dramatic increases and decreases in wave height, respectively, during which noticeable uncertainties in the shoreline hindcast were observed. Therefore, the non-stationary parameters make the model more sensitive to extreme wave conditions.

5.4 Discussion

5.4.1 Model performance

a. Comparison between stationary and non-stationary model

In the coastal sites where the ShoreFor model was applied in the previous studies, most shorelines are recorded at weekly to monthly frequencies (Davidson et al., 2013, Splinter et al., 2014, Splinter et al., 2017, Ibaceta et al., 2022), much lower than the sampling frequency at Hasaki Beach. According to the Nyquist theorem, the sampling frequency should be at least twice the frequency of the signal to avoid aliasing. This implies that sites with lower sampling frequencies may not capture high-frequency shoreline variations accurately.

During model calibration at Hasaki Beach, the model with stationary parameters was applied to high-frequency data. This model could not capture extreme events and underestimated shoreline variations because it is not designed to handle multiple time scales of shoreline change. In calibration, the model is optimized to fit the data's cyclic pattern over longer time scales (e.g., seasonal variations) to minimize the RMSE. Therefore, non-stationary parameters are necessary to enable the equilibrium model to capture extreme events effectively.

The non-stationary model demonstrates superior capability in capturing shoreline variability compared to the stationary model, as evidenced by both hindcast and validation results. In the hindcast period, the non-stationary model successfully reproduced intense shoreline variations from 2003 to late 2007, achieving a notably higher correlation coefficient ($R = 0.610$) compared to the stationary model ($R = 0.36$). This improved performance is further supported by the variance analysis, where the non-stationary model captured more than twice the observed variability compared to the stationary model. In the validation period, while the stationary model showed lower RMSE values, the non-stationary model better reproduced extreme events, as evidenced by the quantile-quantile plot and histogram of shoreline positions (Figure 5.8(b, d)). This aligns with previous findings from model blind tests where equilibrium models typically underestimate shoreline variations (Montaño et al., 2020). The enhanced ability to capture extreme events is particularly valuable for coastal management, as these events often have more significant impacts on shoreline evolution than average conditions. The trade-off between lower RMSE and better representation of extreme events suggests that traditional error metrics alone may not fully represent model performance for coastal management applications.

The performance of the ShoreFor model could be constrained by its fundamental assumption that shoreline changes are predominantly wave-driven. In reality, shoreline evolution is governed by multiple complex processes beyond wave forcing. At Hasaki beach, several factors contribute to this complexity. First, the beach profile measurements are limited to a single cross-section, potentially missing three-dimensional morphological changes such as cusp migration and local scouring behind pier piles. The model shows mismatches with observations during certain periods (late 2012 to mid-2013 and around the end of 2015), which could be attributed to these local morphological changes that are not captured by the wave-driven model. When the shoreline changes are driven by non-wave factors, the model may predict trends opposite to observations, and these discrepancies cannot be resolved through parameter optimization alone. This limitation particularly affects the non-stationary model, where the increased flexibility in parameter variation may amplify the discrepancies between modeled and observed shoreline positions, resulting in higher RMSE compared to the stationary model. For future studies, the implementation of complementary beach monitoring approaches, such as combining satellite imagery with traditional plumb-line measurements, could help better capture and distinguish various beach processes.

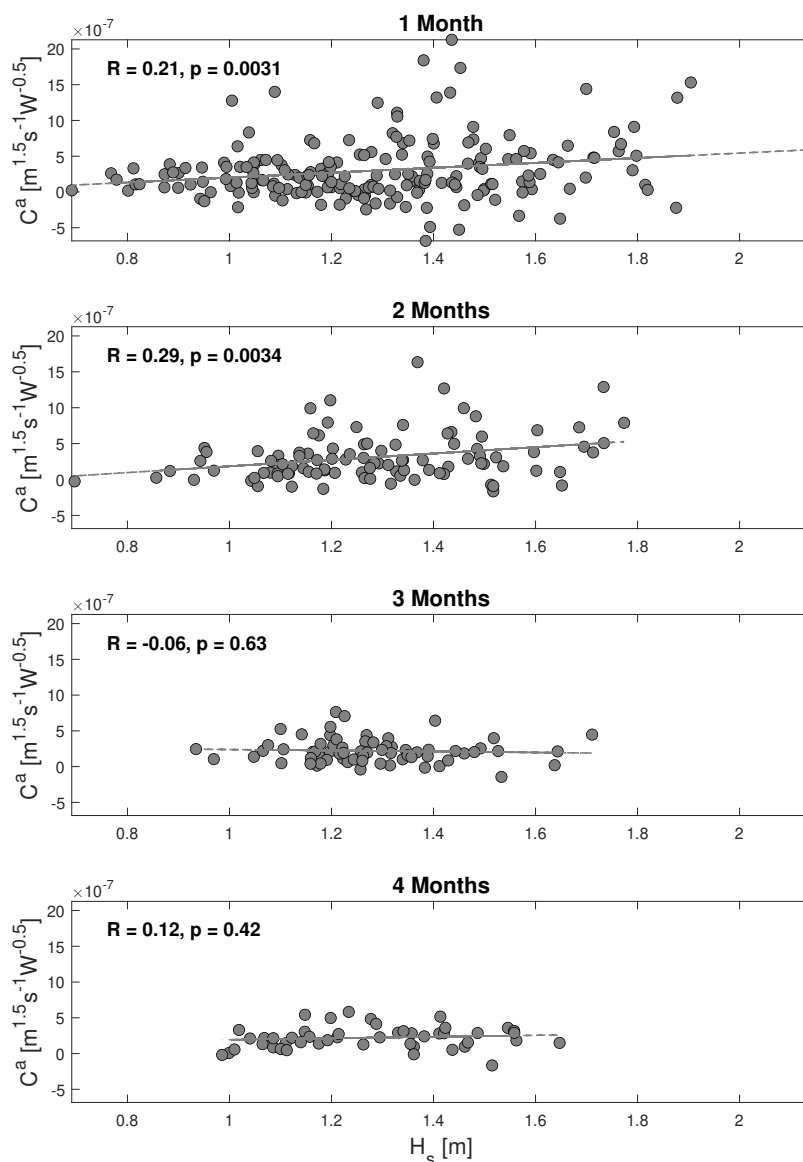


Fig. 5.9 Relationship between C^a and H_s with segment length ranging from 1 to 4 months. The dashed line represents the linear regression fit.

b. Influence of segment length on parameter estimation

The erosion/accretion efficiency coefficients C^e and C^a are assumed to be constant within each segment. If the segment length is too short, there may not be enough shoreline observations to calculate the best-fit coefficients accurately. Conversely, suppose the segment length is too long. In that case, the monthly averaged wave conditions may not

be sufficiently distinct among segments, making it difficult to establish a clear relationship between wave conditions and C^a and C^e .

Figure 5.9 illustrates the relationship between the accretion efficiency coefficient C^a and significant wave height H_s across different segment lengths. As the segment length increases, the range of H_s variation narrows because it is averaged over the segments. This averaging reduces the apparent correlation between C^a and H_s . The linear regression analysis shows that the impact of H_s becomes less significant when the segment length exceeds 2 months, as indicated by the p values. Longer segment lengths filter out seasonal variations in wave height, leading to a more constant distribution of C^a . In extreme cases, where the segment length matches the calibration period, C^a will be the same as in the stationary case.

Therefore, given the pronounced monthly variations in wave conditions at Hasaki Beach, monthly segmentation is deemed suitable for calibrating and validating the equilibrium model in this study.

c. Choice of wave-forcing variants

The choice of wave-forcing variants is crucial in the equilibrium model, as it determines the relationship between wave conditions and shoreline position. In this study, significant wave height H_s and dimensionless settling velocity Ω consistently show better performance compared to wave energy P across both hindcast and validation periods. In the hindcast period, H_s demonstrates superior performance in the non-stationary model ($R = 0.61$, $RMSE = 9.71$) compared to other variants. During validation, Ω achieves the best results in the stationary case ($R = 0.42$, $RMSE = 7.26$), while H_s shows optimal performance when incorporating wave-parameter relationships in the non-stationary model ($R = 0.42$, $RMSE = 8.34$). According to the modeled results of three wave-forcing variants (Figure 5.4, 5.8 and Appendix B), during the regression step, all three wave-forcing variants show a statistically significant relationship with the accretion efficiency coefficients C^a . In terms of C^e , the scatters of Ω show less convergence compared to H_s and P , particularly at values above the average forcing variant. In the shoreline projection step, the models using Ω and P exhibit much greater uncertainties introduced by the regression parameters, which could lead to more uncertainties in future projections and influence the decision-making process. The consistent performance of H_s across both hindcast and validation periods suggests it may be a more reliable choice for long-term shoreline prediction. It is also worth noting that the choice of forcing variants could lead to different erosion and accretion patterns because of the magnitude of disequilibrium in erosion and accretion. For instance, models using P as the forcing variant are highly sensitive to high-energy storm

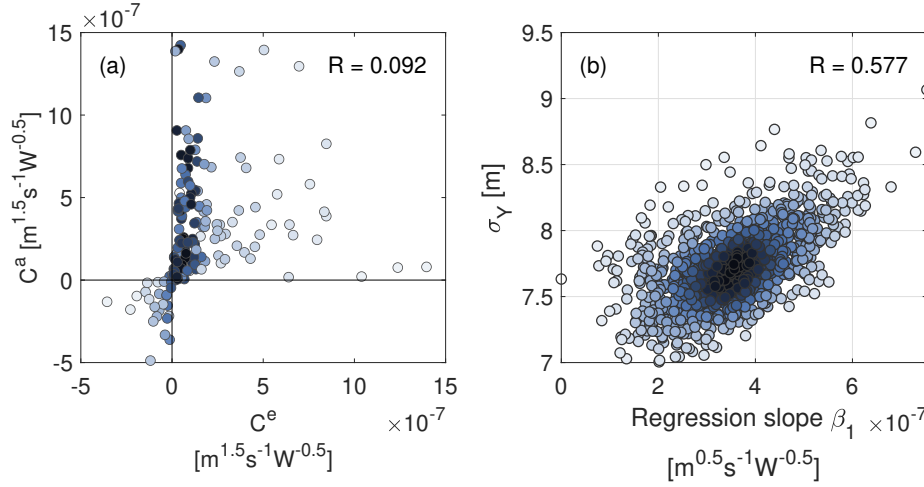


Fig. 5.10 (a) Scatter plot of the accretion efficiency coefficient (C^a) and erosion efficiency coefficient (C^e) for all segments, showing a correlation coefficient of 0.088. (b) Scatter plot of the slope β_1 of the regression line of C^a and H_s against the standard deviation σ_Y of shoreline hindcast during validation for all bootstrap ensembles. The color indicates the distribution density of the data points.

events, leading to significant erosion, while potentially overlooking shoreline fluctuations during moderate or low-energy conditions. In summary, selecting the forcing variant significantly influences the model's behavior and outcomes, with H_s showing the most consistent and reliable performance across different temporal scales and analysis periods.

In previous studies by Davidson et al. (2013) and Splinter et al. (2014), dimensionless settling velocity Ω was used as the wave-forcing variant since Ω is a standardized parameter that can be easily compared between sites. However, the results of this study at Hasaki Beach suggest that H_s is sufficient to represent wave conditions at Hasaki Beach for local projection purposes. There is no significant difference in model results using Ω and H_s . Therefore, wave-forcing variants should be chosen based on the site-specific wave conditions when applying the model at different sites.

5.4.2 Non-stationarity of model parameters

a. Correlation analysis of efficiency coefficients

The calibrated parameters C^a and C^e , representing the shoreline change efficiency coefficients in Eq. (5.1), indicate how sensitive the shoreline change rate is to disequilibrium conditions. As discussed earlier, incorporating non-stationary parameters allows the model to better capture extreme accretion and erosion events. Therefore, exploring the

non-stationarity of these calibrated parameters could provide valuable insights into the underlying physical processes governing shoreline changes.

From the scatter plots of C^a and C^e against significant wave height H_s (Figure 5.4), the erosion coefficient C^e shows no significant correlation with wave height, while the accretion coefficient C^a exhibits a weak positive correlation. Similarly, in the time series of C^a (Figure 5.3), higher C^a values typically occur during high wave periods.

This result suggests that erosion efficiency remains relatively constant, indicating that the erosion rate is primarily related to the current disequilibrium, a relative concept induced by incoming waves rather than the absolute significant wave height. On the other hand, the positive correlation between accretion efficiency and wave height indicates that higher wave heights accelerate the accretion rate. This finding at Hasaki beach contrasts with the results of Ibaceta et al. (2022), who reported a negative correlation between accretion/erosion efficiency and dimensionless settling velocity Ω at Gold Coast, Australia.

The period segment-averaged wave height serves as a "background" wave condition, showing a positive correlation with the accretion efficiency. This correlation indicates that with the same value of positive disequilibrium (i.e., when wave conditions calm down), the accretion process is more efficient during periods characterized by higher background waves compared to periods of lower waves. One possible explanation for this relationship could be the sediment availability in the water column. During periods with higher wave heights, the sediment environment might become more active, potentially resulting in more sediment being suspended in the water column. Additionally, sustained high wave run-up, which is more likely to occur in high-wave periods, might also contribute to accelerated accretion. However, these mechanisms require further investigation to confirm their roles in the observed correlation.

In contrast, erosion efficiency is more related to the availability of erodible sediment. According to in-situ sediment sampling (Banno et al., 2013), the sediment at Hasaki Beach is generally vertically homogeneous and fine-grained from sea bottom downward, which may explain the constant erosion efficiency. The correlation between accretion efficiency C^a and erosion efficiency C^e is weak, with no evident linear relationship observed between them (Figure 5.10(a)), which is in agreement with Ibaceta et al. (2020) and D'Anna et al. (2021)). This suggests that the accretion and erosion efficiency coefficients in the equilibrium model's calibration need to be calibrated separately rather than using one coefficient and a ratio to represent the other.

b. Implications for model physics and calibration

It is worth noting that C^e exhibits wider scatter under low wave height conditions (Figure 5.4). This pattern could potentially be explained by the compensation mechanism: during periods of low wave energy when wave effects become relatively lower, the effect of other processes might be implicitly absorbed into the C^e parameter. This could possibly explain the observed extreme values of C^e under low wave conditions.

The observed linear relationship between H_s and C^a introduces a quadratic term into the governing ODE (Eq. (5.1)), which raises fundamental questions about how the model represents beach accretion processes. This quadratic ODE challenges the understanding of whether the exponential time scale to equilibrium remains valid for accretion. Interestingly, the lack of a similar relationship for C^e suggests that the model representation of erosion processes may still be valid. Further investigation at different sites is needed to fully understand these contrasting behaviors in accretion and erosion processes and their implications for shoreline modeling.

To calibrate the accretion and erosion efficiency coefficients, the regression slopes β_1 of C^a and H_s are calculated for each ensemble by the bootstrap resampling process. The standard deviation of modeled shorelines σ_Y in validation is then compared with the regression slopes (Figure 5.10(b)). The positive correlation indicates that the model shoreline is sensitive to the regression slope β_1 . Specifically, a higher regression slope β_1 is associated with higher shoreline variance, resulting in a more fluctuated shoreline. One possible interpretation is that the regression slope β_1 reflects an intrinsic characteristic of the beach. For example, if the sediment in a coastal area is finer, meaning it is more mobile and easier to transport, this could potentially result in a steeper regression slope β_1 . However, this is just a hypothesis, and the physical interpretation of the regression slope β_1 requires further investigation. A clearer understanding of underlying physics can be achieved by comparing the morphodynamic behavior at different sites and collecting more information about local sediment conditions (e.g., vertical sorting and compositions). In this way, the sediment conditions are better considered by the regression slope β_1 instead of a fixed sediment settling velocity w in Ω .

Overall, the segmentation analysis demonstrated that treating efficiency coefficients, particularly the accretion coefficient (C^a), as constant parameters is fundamentally inadequate given their highly variable nature. This variability prompted us to investigate potential relationships between these parameters and wave conditions, leading to the implementation of a linear relationship between C^a and significant wave height H_s in our non-stationary model. While this approach showed only marginal improvements in conventional evaluation metrics compared to its stationary counterpart, it exhibited

enhanced capability in reproducing extreme erosion and accretion events when using H_s as the forcing variant. Meanwhile, it is important to acknowledge that other functional relationships may exist but remain unexplored for future research.

Chapter 6

Shoreline projection under climate change

6.1 Future wave climate analysis

6.1.1 climate change and GCM

To assess future shoreline evolution under climate change conditions, reliable projections of wave climate are essential. This study employs a chain of numerical models to generate seamless wave projections from 1950 to 2099, following the approach of Shimura et al. (2022) as shown in Figure 6.1.

The climate simulations are conducted using the Japanese Atmospheric General Circulation Model (MRI-AGCM; Mizuta et al., 2012), which features one of the highest spatial resolutions (0.1875°) among current global climate models (GCMs). The model uses monthly averaged sea surface temperature (SST) and sea ice concentration (SIC) as bound-

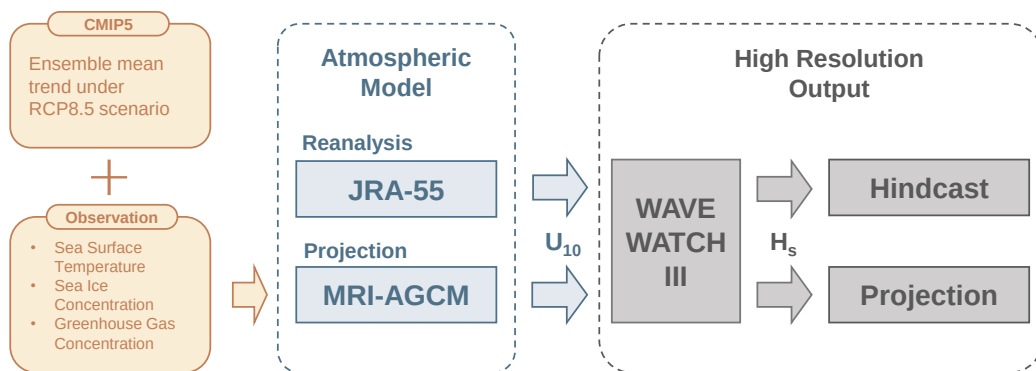


Fig. 6.1 Wave hindcast and projection flow chart

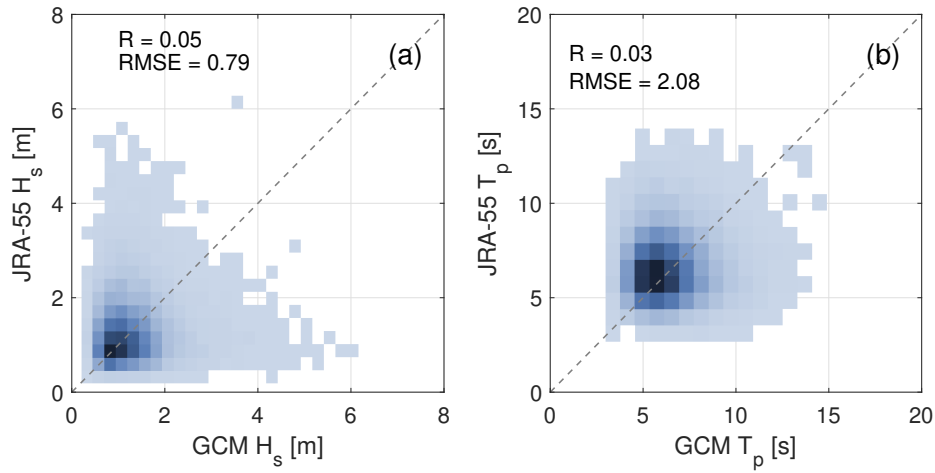


Fig. 6.2 Scatter plot comparing wave parameters between JRA-55 and GCM (1986-2018): (a) significant wave height (H_s) and (b) peak wave period (T_p). Color intensity indicates data density.

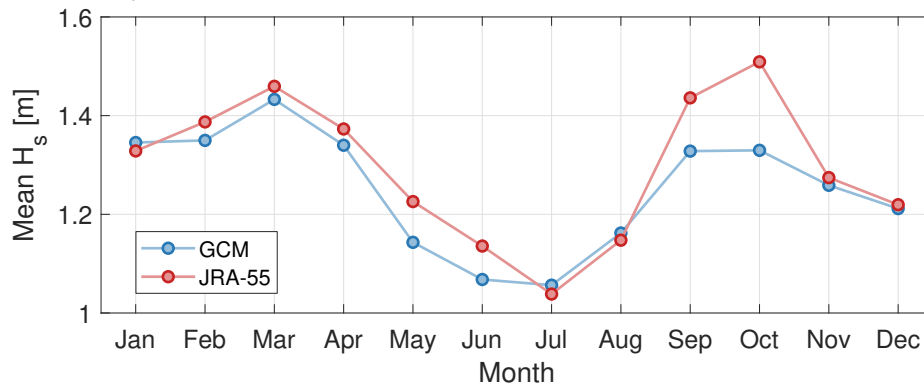


Fig. 6.3 Monthly averaged significant wave height (H_s) from JRA-55 and GCM simulations during 1986-2018.

ary conditions, along with prescribed greenhouse gas concentrations. To incorporate climate change effects, the CMIP5 multi-model ensemble (Taylor et al., 2012) is used to estimate long-term trends in SST and SIC under the RCP8.5 scenario, the most severe emission pathway. These trends are then added on historical observations from 1979-2014 to create future boundary conditions. The MRI-AGCM generates diagnostic hourly 10-meter wind fields (U_{10}) that reflect both historical variability and projected climate change impacts. These wind fields, combined with monthly SIC data, drive the WAVEWATCH III model to simulate wave conditions. The wave model is configured with fine resolution in the western North Pacific (0.13° latitude $\times$ 0.15° longitude), providing detailed wave predictions for the Hasaki Beach region over the entire 150-year period. The wave data at the nearest grid point at 35.81°N , 140.8°E is extracted for validation and projection.

6.1.2 Validation and projection

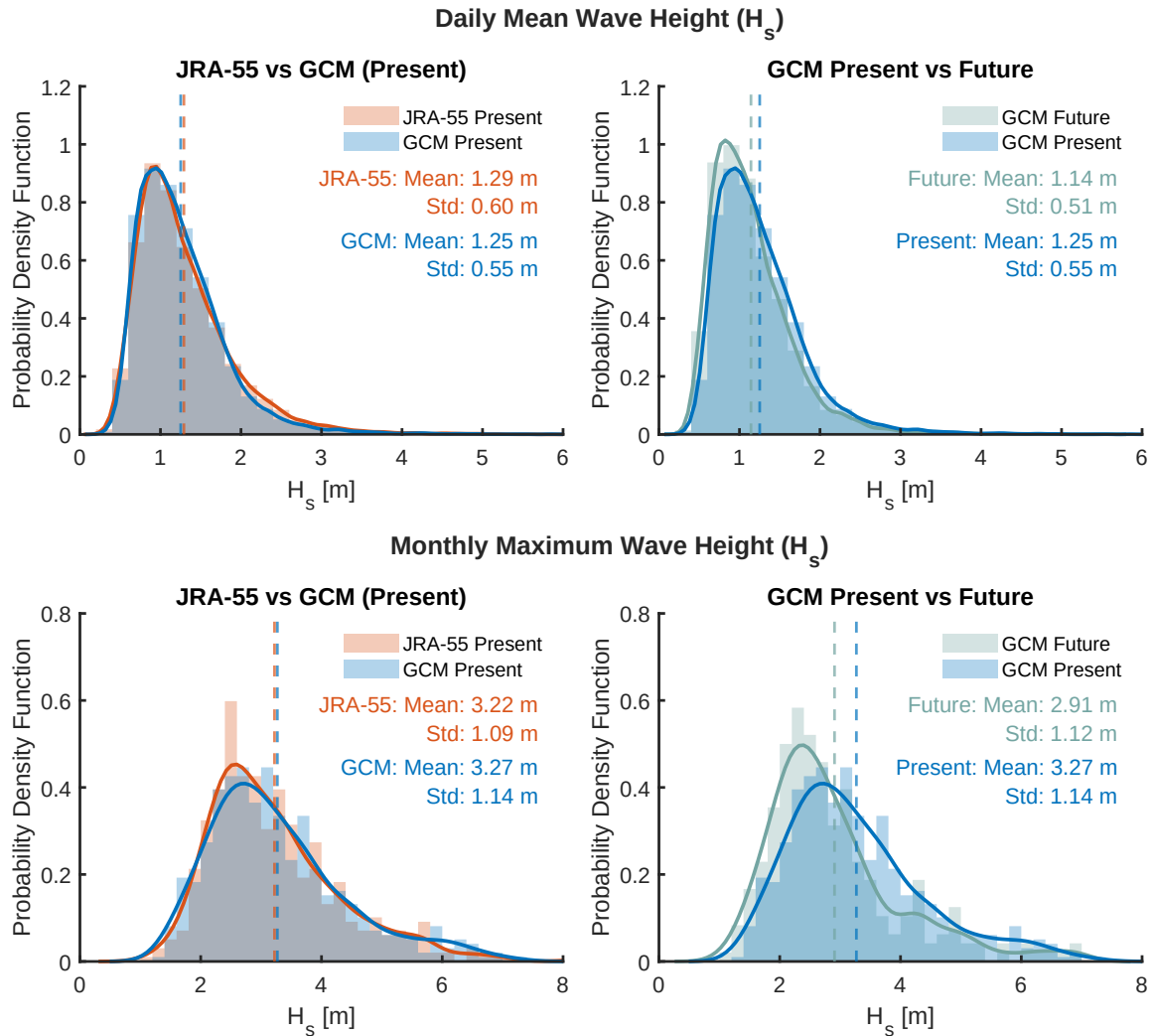


Fig. 6.4 Probability density functions of wave heights (H_s). Top panels: daily mean H_s comparing JRA-55 and GCM present climate (left), and GCM present versus future climate (right). Bottom panels: monthly maximum H_s with the same comparisons. Dashed lines indicate mean values.

The wave conditions used in previous shoreline analyses were derived from the JRA-55 atmospheric reanalysis model (Section 3.2.1), which has been well-calibrated and validated against in-situ observations. To assess the reliability of future projections, we first compare the wave characteristics between JRA-55 and MRI-AGCM (hereafter GCM) for the overlapping period 1986-2018. The comparison of seasonal averaged hourly wave parameters shows limited correlation between the two datasets (Figure 6.2), with correlation coefficients (R) of 0.05 and 0.03 for significant wave height (H_s) and peak

period (T_p) respectively. The weak correlation is expected as the GCM, being a climate model rather than a reanalysis product, is not designed to reproduce the exact time series of historical events. The GCM successfully captures the statistical seasonal wave patterns at Hasaki Beach (Figure 6.3), demonstrating both annual and semi-annual cycles. Both datasets exhibit remarkable agreement in capturing the minimum wave height in July (approximately 1.0 m) and the characteristic dual-peak seasonal variation. However, the GCM notably underestimates the influence of typhoons during the autumn season, resulting in lower peak wave heights in September and October compared to JRA-55 data, where monthly averaged wave heights reach up to 1.5 m.

To quantitatively assess the model's performance and future projections, we analyzed the probability density functions (PDFs) of significant wave heights (H_s) (Figure 6.4). This analysis encompasses both daily mean and monthly maximum wave heights, comparing the GCM outputs with JRA-55 reanalysis data for present climate conditions, as well as examining projected changes in wave climate between present and future periods. The statistical distributions of wave parameters show good agreement between the two datasets (Figure 6.4, left panels). The probability density functions (PDFs) of daily mean H_s are notably similar between JRA-55 (mean: 1.29 m, std: 0.60 m) and GCM (mean: 1.25 m, std: 0.55 m) for the present climate (1986-2018), with differences of only 0.04 m in mean height and 0.05 m in standard deviation. For monthly maximum H_s , the GCM shows minor overestimation for both small waves ($H_s < 2$ m) and extreme events ($H_s > 6$ m), but these differences are not statistically significant. This is reflected in the slightly higher GCM values (mean: 3.27 m, std: 1.14 m) compared to JRA-55 (mean: 3.22 m, std: 1.09 m), with minimal differences of 0.05 m in both mean and standard deviation. Comparing present (1986-2018) and future (2070-2099) wave climates simulated by the GCM reveals notable changes (Figure 6.4, right panels). The PDF of daily mean H_s shifts toward lower values in the future climate, with the mean decreasing from 1.25 m to 1.14 m and the standard deviation reducing from 0.55 m to 0.51 m, indicating both generally milder wave conditions and reduced variability. This trend is more pronounced in the monthly maximum H_s distribution, where the probability of waves exceeding 3 m decreases substantially, with the mean dropping from 3.27 m to 2.91 m and a slight decrease in standard deviation from 1.14 m to 1.12 m. These projected changes align with the findings of Shimura et al. (2022), who reported a projected decrease in tropical cyclone frequency in the Western North Pacific under the RCP8.5 scenario, though individual storms may become more intense.

6.2 Future shoreline assessment

6.2.1 Methodology

To assess future shoreline change under climate change conditions, we apply the non-stationary model with H_s as the forcing variant to the GCM wave projections. The model parameters calibrated in Section 5.3.2 (Table 5.2) are used for the entire calculation period from 1991 to 2099. While the efficiency coefficients C^a and C^e are allowed to vary, other parameters remain fixed, including the response factor ϕ and the linear trend term b .

In long-term simulations, the modeled shoreline occasionally exhibits persistent directional drift (erosion or accretion), suggesting that the fixed linear term b may no longer adequately represent long-term processes under changed wave conditions. As this study focuses primarily on short-term shoreline variability driven by cross-shore sediment transport, we employ two methods to remove these long-term trends from the modeled shoreline positions to better evaluate the shoreline variability in the future.

The first approach uses Discrete Wavelet Transform (DWT) with a bior3.9 wavelet, previously validated in Section b.. DWT automatically identifies and separates long-term components without requiring manual identification of drift periods. By removing approximation coefficients above level 5 (corresponding to time scales longer than approximately 5 years), we can effectively isolate shorter-term variations while preserving energy. However, since DWT results are sensitive to high-frequency fluctuations, the modeled shoreline positions are first averaged monthly before applying the transform.

The second approach employs moving windows of varying sizes to analyze shoreline variability between present (1991-2018) and future (2070-2099) climate periods. Window sizes ranging from 5 to 15 years are applied, with the window advancing one year at a time. Within each window, a linear regression is fitted and subtracted to detrend the data, and variance is calculated for the residuals. This method preserves the original temporal resolution of the modeled shoreline positions and provides a more direct measure of short-term variability compared to DWT.

6.2.2 Results

The detrended shoreline positions obtained through both DWT and moving window analyses reveal significant changes in shoreline variability under future climate conditions as shown in Figure 6.5. The DWT-filtered shoreline (Figure 6.5, top panel) shows consistent short-term fluctuations throughout the simulation period, with amplitudes typically ranging from -20 to 20 meters. However, the temporal evolution of variance, calculated

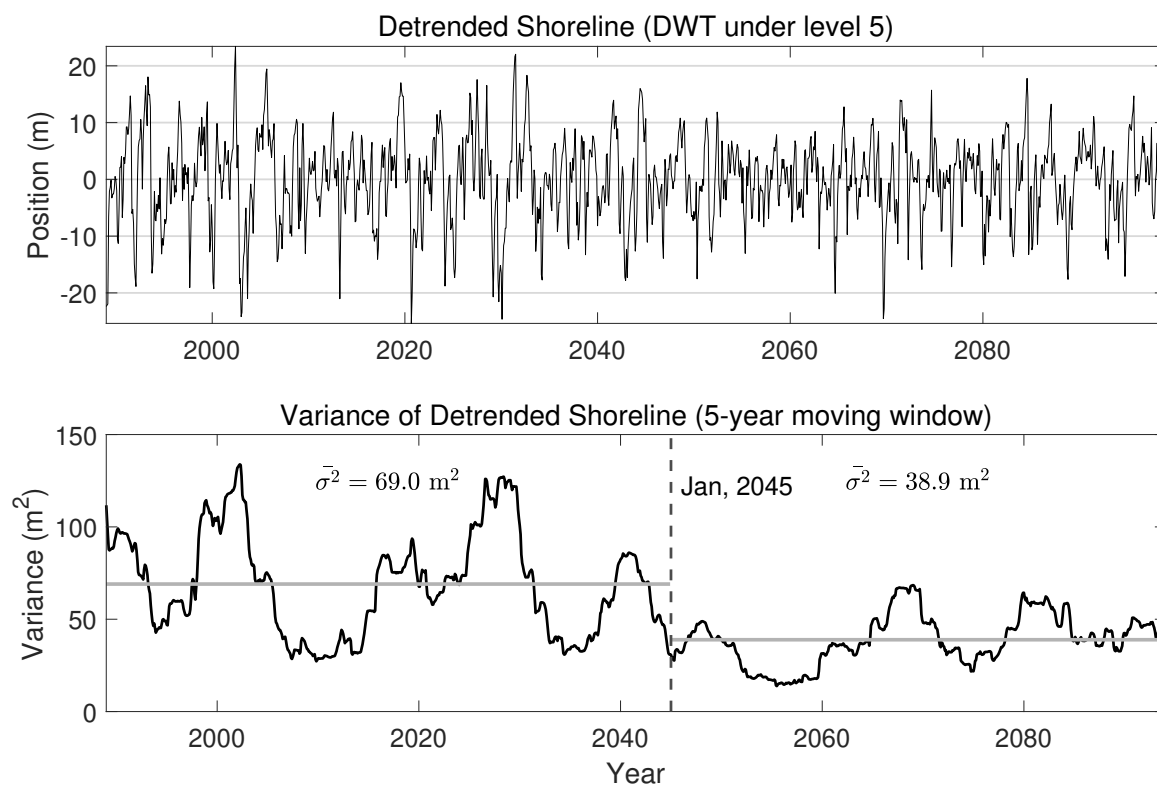


Fig. 6.5 Time series of detrended shoreline positions. Top panel: shoreline positions after removing trends using DWT below level 5. Bottom panel: variance of the detrended shoreline calculated using a 5-year moving window, with mean values before and after January 2045 indicated by grey lines.

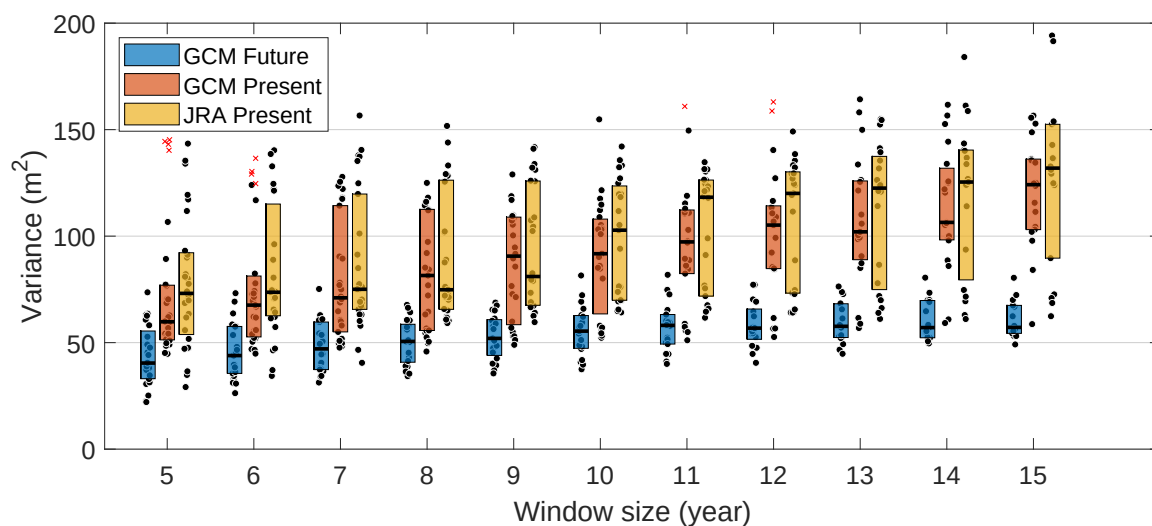


Fig. 6.6 Comparison of shoreline position variance across different moving window sizes for three datasets: GCM Future (2070-2099), GCM Present (1991-2018), and JRA-55 Present (1991-2018).

using a 5-year moving window (Figure 6.5, bottom panel), indicates a significant decrease in shoreline variability after 2045. The average variance decreases from 69.0 m² before 2045 to 38.9 m² in the latter half of the century, suggesting reduced shoreline variability under future climate conditions.

This reduction in variability is further confirmed by the moving window analysis across different temporal scales as shown in Figure 6.6. By comparing the present climate periods, we observe that shoreline variations driven by GCM wave conditions show good agreement with those from JRA-55 reanalysis, albeit with a systematic bias. This agreement is particularly evident for window sizes between 7 and 10 years, where the variance distributions from GCM Present and JRA-55 Present substantially overlap. The consistent reproduction of historical shoreline variability by GCM demonstrates its capability to generate wave conditions that produce realistic shoreline behavior, supporting the reliability of its future projections. Under future climate conditions (GCM Future), the model shows a significant decrease in variance compared to both present-day simulations. This reduction becomes more pronounced with increasing window size, indicating that the projected decrease in shoreline variability is robust across multiple temporal scales.

These results align with the previously observed changes in wave climate, particularly the projected decrease in tropical cyclone frequency and the overall reduction in extreme wave events in the Western North Pacific region under future climate conditions.

6.2.3 Discussion

a. Variance change

Both DWT (Figure 6.5) and moving window analyses (Figure 6.6) consistently indicate that Hasaki Beach is projected to experience reduced shoreline variability under the RCP8.5 scenario, primarily due to decreased tropical cyclone frequency in the Western North Pacific region. The projected wave climate shows a notable reduction in monthly maximum wave heights, with this decrease being more pronounced than the reduction in daily mean H_s (Figure 6.4). This change in wave patterns results in smaller disequilibrium conditions during both high and low wave periods, which explains the observed reduction in shoreline variability.

The 5-year moving window analysis (Figure 6.6) shows similar variance estimates to the DWT method (Figure 6.5, bottom panel), as both approaches effectively filter out components with time scales longer than 5 years. For present climate conditions, both GCM and JRA-55 simulations show that shoreline variance increases substantially with larger window sizes. In contrast, under future climate conditions, the variance

increases more gradually with window size and stabilizes beyond 10 years. This difference suggests that present wave conditions drive not only significant annual variations but also substantial interannual variability extending beyond 5 years. The larger variance at longer time scales in the present climate reflects more pronounced interannual changes in wave conditions compared to the future projections, where wave characteristics are expected to show less year-to-year variability.

However, it is important to note that the source of interannual shoreline changes remains uncertain. While our analysis focuses on cross-shore transport driven by wave-induced disequilibrium, long-term shoreline behavior may also be influenced by long-shore sediment transport processes. Future research should aim to better distinguish between these mechanisms and their relative contributions to shoreline variability across different time scales. This understanding will be crucial for improving long-term shoreline predictions under changing climate conditions.

b. Limitations and outlooks

The projection of shoreline variability in this study relies on the linear relationship between wave conditions and efficiency coefficients established under present climate conditions. As discussed in Section 5.4, shoreline variability is proportional to this linear regression slope, which may be influenced by local sediment characteristics. Our projections assume this relationship remains constant, implying unchanged sediment conditions throughout the simulation period. However, sandy beaches are dynamic systems characterized by complex interactions between hydrodynamic forcing and morphological response. Under the projected milder wave conditions at Hasaki Beach, finer sediments are likely to accumulate in the upper shoreface. These finer sediments would be more sensitive to wave energy, potentially increasing shoreline variability and partially counteracting the reduced wave forcing. Therefore, future studies should consider the co-evolution of wave climate and beach sediment characteristics when evaluating shoreline response to climate change.

A significant limitation of this study is the exclusion of sea-level rise (SLR) effects, which represent a primary impact of climate change on coastal systems. While the precise mechanisms linking SLR to shoreline change remain debated, current projections indicate global mean sea level could rise by 0.63-1.01 m under the SSP5-8.5 scenario by 2100 (IPCC, 2023). SLR can influence shoreline dynamics through multiple processes. These include changed beach profile equilibrium conditions, wave run-ups, and sediment transport gradients. Future research should investigate these combined effects of changing wave climate and SLR on shoreline evolution.

Additionally, our projections are based on a single seamless climate simulation, which does not account for wave climate uncertainty. Future studies could employ ensemble approaches, similar to Vitousek et al. (2021), to quantify projection uncertainties from both wave climate and SLR. Such analysis could identify when SLR-induced uncertainty becomes dominant over wave-induced uncertainty in shoreline predictions. This transition point would be particularly valuable for coastal management, helping communities develop effective adaptation strategies. Understanding these relative uncertainties would enable more informed decisions about the timing and type of coastal protection measures needed. Communities could better balance immediate erosion management needs with long-term SLR adaptation planning, and develop more robust frameworks for coastal infrastructure development. This understanding of uncertainty evolution would ultimately support more effective and economically efficient coastal zone management under climate change conditions.

Chapter 7

Conclusions

This research utilized a unique 33-year dataset from Hasaki Beach to advance our understanding of shoreline morphodynamics and improve predictive modeling capabilities. Through comprehensive analysis across multiple temporal scales, we developed an enhanced equilibrium shoreline model that better captures beach response to varying wave conditions and provides insights into potential future shoreline behavior under climate change scenarios.

Analysis of the high-frequency measurements revealed that using Mean High Water level as the shoreline reference position provided optimal correlation with wave conditions ($R = -0.37$). This finding enabled reliable quantification of wave-driven morphological changes. The temporal analysis demonstrated asymmetric patterns between erosion and accretion phases, with storm-induced erosion occurring rapidly (1-2 days) followed by extended recovery periods. Notably, August and September exhibited the highest short-term variability ($\sigma^2 > 40 \text{ m}^2$), nearly double that of other months, despite not coinciding with peak wave energy periods. The application of Discrete Wavelet Transform (DWT) effectively isolated dominant annual and semi-annual cycles while removing long-term trends, and Cross Power Spectral Density analysis revealed clear phase relationships between wave heights and shoreline position.

The development of a non-stationary parameter framework for the ShoreFor model yielded significant improvements in predictive capabilities. While both data assimilation and segmentation approaches were explored, the Ensemble Kalman Filter method struggled to identify clear parameter-wave relationships due to the high-frequency nature of the measurements. In contrast, by segmenting the calibration period (1991-2010) into monthly intervals, we successfully identified distinct relationships between model parameters and wave conditions. The accretion efficiency (C^a) showed a significant positive correlation with wave height ($R = 0.218$, $p = 0.002$), while erosion efficiency (C^e) remained

relatively constant, suggesting fundamentally different mechanisms governing these processes. During the hindcast period (1998-2008), the non-stationary model demonstrated markedly improved performance ($R = 0.61$, $RMSE = 9.71$ m) compared to the conventional stationary approach ($R = 0.36$, $RMSE = 11.45$ m). The model maintained superior performance during the validation period (2011-2015), particularly in capturing extreme events, though with slightly higher RMSE values. Both significant wave height H_s and dimensionless settling velocity Ω consistently outperformed wave power P as forcing variants in both 2-year and 5-year simulations.

The linear relationship between accretion efficiency and wave height introduces a quadratic term in the governing equation, while the consistent superior performance of H_s and Ω over P , which incorporate different powers of wave height, suggests the need to reconsider the fundamental power law structure of the model equations. These findings collectively indicate that the current form of the governing equation may need revision to better represent the underlying physics of shoreline evolution.

Application of this improved model to future climate scenarios using state-of-the-art GCM projections under RCP8.5 revealed decreased shoreline variability after 2045. Following removal of long-term trends (DWT level 5, period > 5.3 years), the average variance decreased from 69.0 m^2 to 38.9 m^2 in the latter half of the century. This 43% reduction primarily reflects projected changes in Western North Pacific storm patterns, particularly decreased tropical cyclone frequency. The probability density functions of wave heights showed a clear shift toward milder conditions when comparing present (1986-2018) and future (2070-2099) periods.

Several limitations warrant consideration. The analysis focused primarily on cross-shore processes at a single profile location, with limited consideration of longshore transport effects and three-dimensional morphological changes. Climate change projections excluded sea-level rise impacts, which could significantly influence future shoreline evolution. Additionally, the future projections assume unchanged sediment characteristics, though wave climate changes could potentially alter grain size distribution and sediment availability in the upper shoreface. While the high-frequency measurements enabled detailed analysis of beach response, such comprehensive datasets remain rare, potentially limiting immediate model application to other sites.

Future research directions should address these limitations through integration of additional coastal processes. Key priorities include incorporating sea-level rise effects and longshore transport into the non-stationary parameter framework, investigating sediment characteristic changes under varying wave climates, and validating these approaches across diverse coastal environments through integration with remote sensing data.

This research demonstrates the substantial value of sustained, high-frequency coastal monitoring programs in advancing our understanding of beach morphodynamics. The improved modeling framework provides a foundation for more accurate shoreline predictions while maintaining computational efficiency, supporting more effective coastal management and adaptation planning under changing climate conditions.

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Appendix A

Discrete wavelet transform

Discrete Wavelet Transform Time Series and Variance - db6

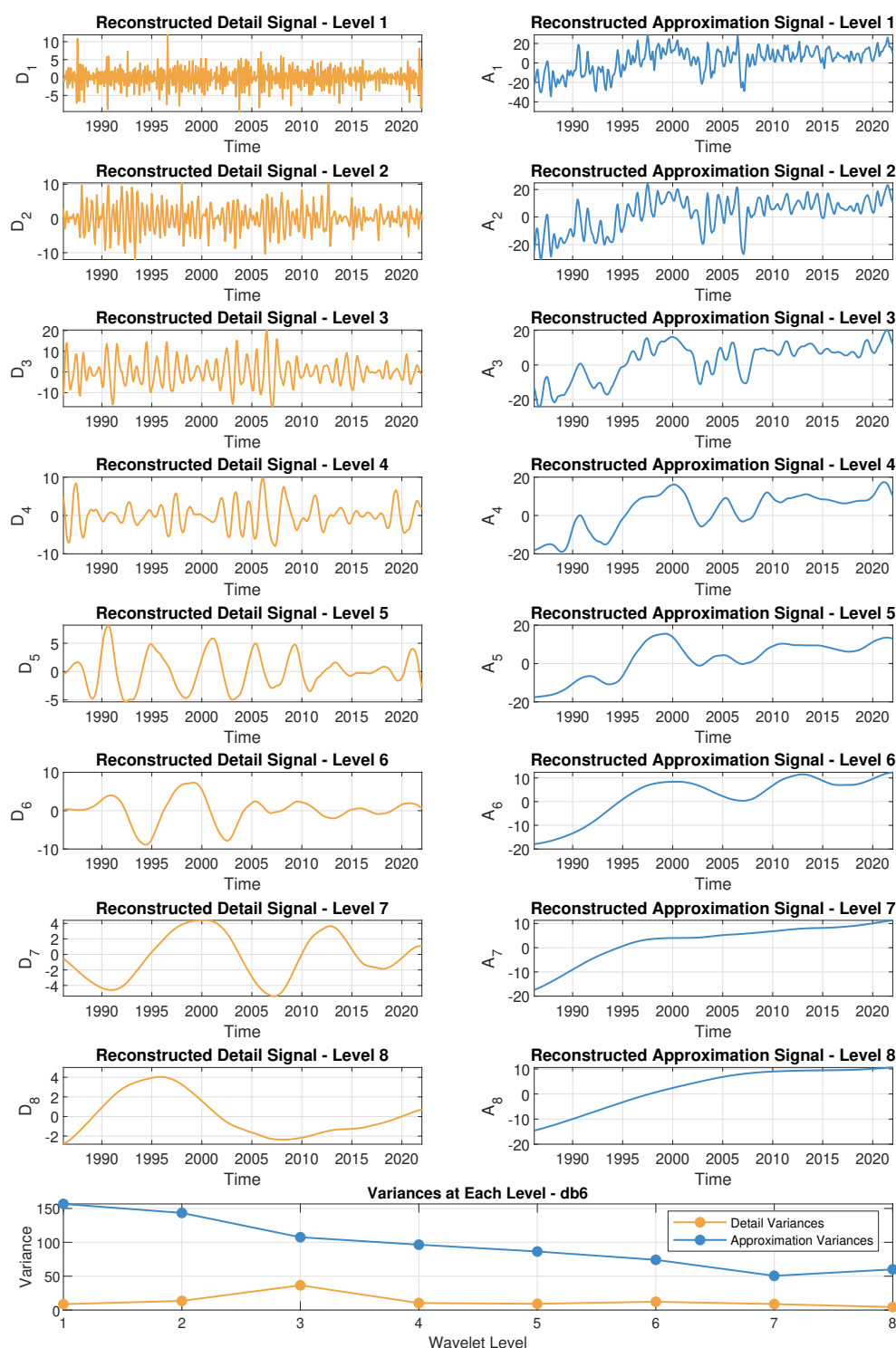


Fig. A.1 Discrete Wavelet Transform decomposition of monthly averaged shoreline position using db6 wavelet. Detail coefficients (D_1 - D_8 , left), approximation coefficients (A_1 - A_8 , right), and their respective variances (bottom) at each decomposition level.

Discrete Wavelet Transform Time Series and Variance - sym6

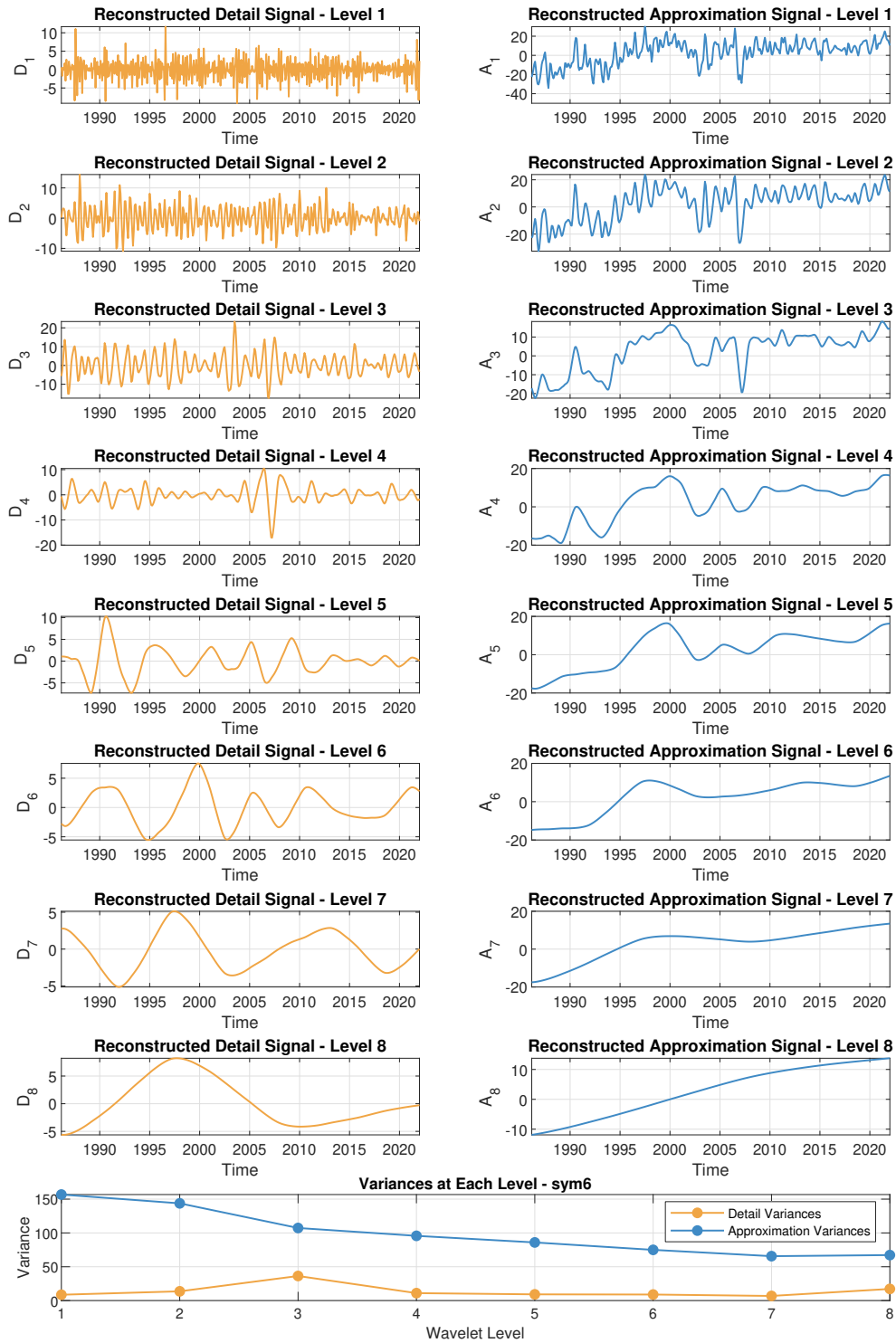


Fig. A.2 Discrete Wavelet Transform decomposition of monthly averaged shoreline position using sym6 wavelet. Detail coefficients (D_1 - D_8 , left), approximation coefficients (A_1 - A_8 , right), and their respective variances (bottom) at each decomposition level.

Appendix B

Non-stationary parameters

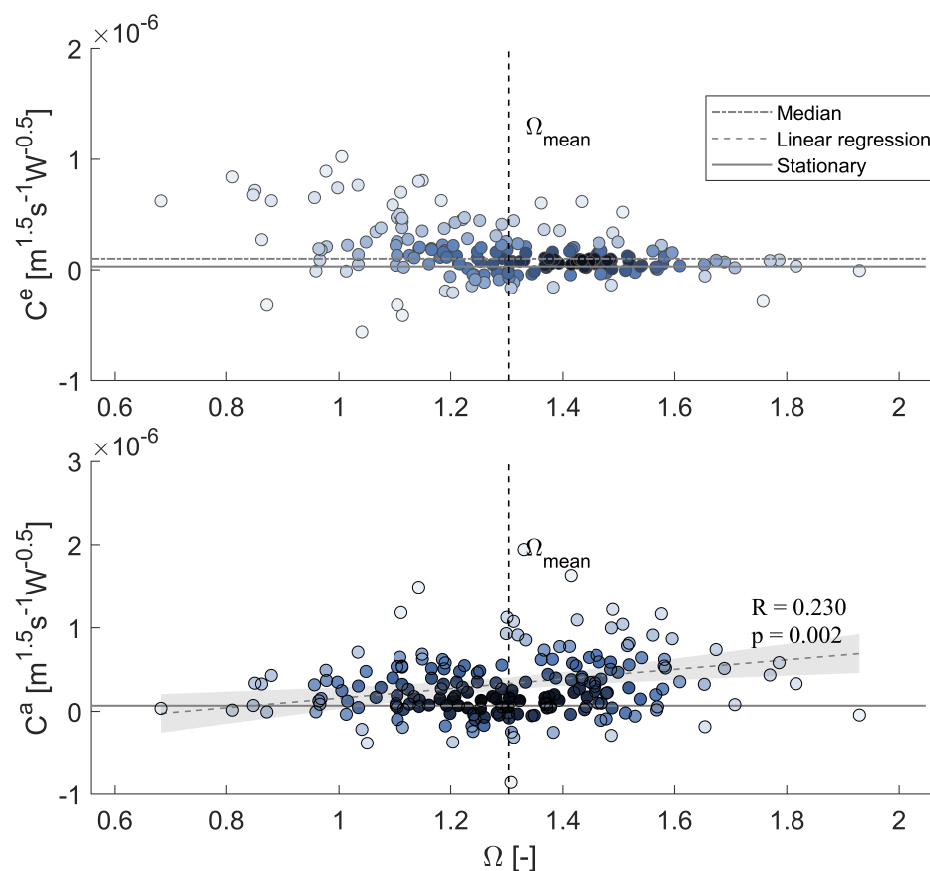


Fig. B.1 Scatter plots showing the relationship between the dimensionless settling velocity (Ω) and the erosion efficiency coefficient (C^e) (top panel) and the accretion efficiency coefficient (C^a) (bottom panel).

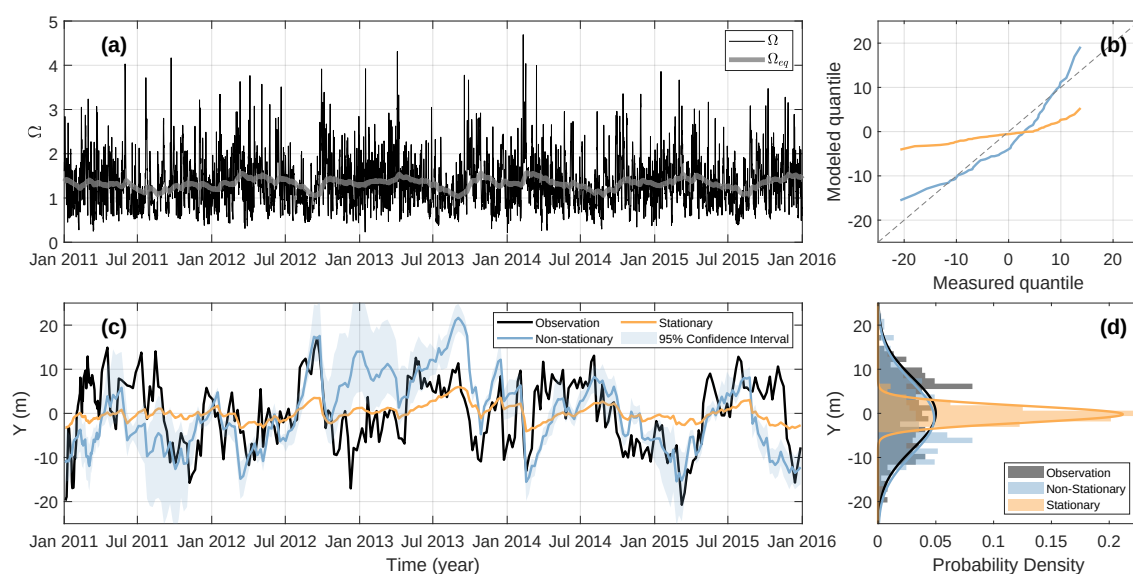


Fig. B.2 Shoreline hindcast using dimensionless settling velocity (Ω)

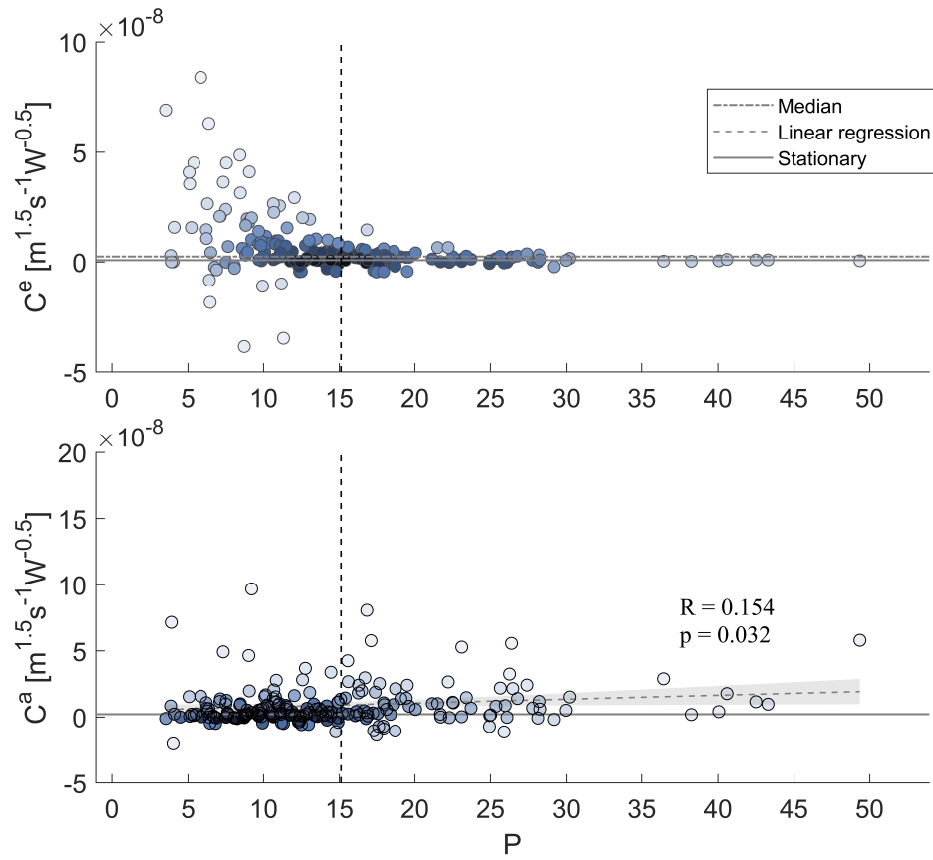


Fig. B.3 Scatter plots showing the relationship between the wave energy (P) and the erosion efficiency coefficient (C^e) (top panel) and the accretion efficiency coefficient (C^a) (bottom panel).

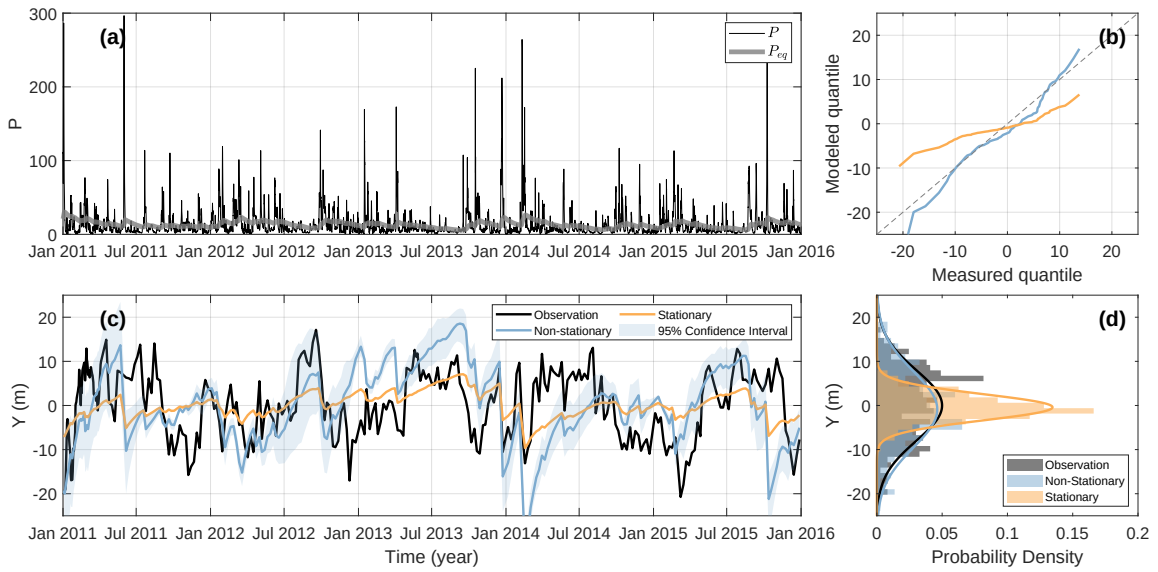


Fig. B.4 Shoreline hindcast using wave energy (P)

