MULTISCALE ASSESSMENT OF SHORELINE EVOLUTION IN THE US PACIFIC NORTHWEST VIA A PROCESS-BASED MODEL

MOHSEN TAHERKHANI[1], MEREDITH LEUNG[2], PETER RUGGIERO[3], SEAN VITOUSEK[4], JONATHAN ALLAN[5]

1. *Department of Civil and Construction Engineering, Oregon State University, 1491 SW Campus Way, Corvallis, OR 97331, USA. taherkhm@oregonstate.edu.*
2. *College of Earth, Ocean, and Atmospheric Sciences, Oregon State University, 2651 SW Orchard Avenue, Corvallis, OR 97331, USA. leungmer@oregonstate.edu.*
3. *College of Earth, Ocean, and Atmospheric Sciences, Oregon State University, 2651 SW Orchard Avenue, Corvallis, OR 97331, USA. Peter.Ruggiero@oregonstate.edu.*
4. *Pacific Coastal and Marine Science Center, US Geological Survey, 2885 Mission St, Santa Cruz, CA 95060, USA. svitousek@usgs.gov.*
5. *Oregon Department of Geology and Mineral Industries, Newport Field Office, P.O. Box 1033, Newport, OR 97365, USA. jonathan.allan@dogami.oregon.gov.*

Abstract: Prediction of shoreline evolution in coastal environments is critical to aid adaptation strategy planning for coastal communities. To perform reliable predictions, process-based shoreline change models have recently gained popularity in many applications. The study region here, Tillamook County, Oregon, on the US Pacific Northwest coast, has recently been experiencing elevated shoreline erosion rates. The inherent uncertainties driving coastal change, e.g., sea-level rise and changing patterns of storminess, emphasize the need for robust shoreline evolution predictions in this region. To this end, we applied CoSMoS-COAST, an ensemble data-assimilated shoreline model that simulates short- and long-term shoreline change processes. We calibrated and validated the model using the hindcasted wave time series and observed shoreline positions and found a strong correlation between the number of observed shoreline positions and the model's hindcasting skill. Moreover, results revealed an alongshore close-to-uniform shoreline change rate in the past several years, mainly driven by short-term, wave-driven processes. So far CoSMoS-COAST has performed satisfactorily with the spatially sparse supply of quality historical shoreline positions in our application. Moreover, this model resolves various components (e.g., short- and long-term processes) in the shoreline change sufficiently. This study represents a starting point in the long-term projection of shoreline evolution throughout the entire PNW (Oregon and Washington) coastline since Tillamook County features the majority of the coastal settings present in other coastal regions in the PNW.

Introduction

Beaches serve as the first line of defense in coastal environments, acting as buffers against various coastal hazards, e.g., coastal flooding and dune/bluff erosion. Thus, accurate and reliable quantitative predictions of shoreline evolution are of paramount importance to inform adaptation planning measures and enhance coastal resiliency (Nicholls et al., 2016; Montaño et al., 2020). Shoreline evolution typically occurs at several time scales, ranging from days/weeks (e.g., storm-driven erosion events; usually recoverable) to decades (e.g., chronic erosion; usually irrecoverable) (Vitousek et al., 2022b). Therefore, it is crucial to incorporate various processes in predictive modeling efforts since shoreline evolution is often driven by short-term (e.g., cross-shore sediment transport) and long-term (e.g., longshore sediment transport and sea-level rise-induced shoreline migration) processes (Montaño et al., 2020) and their physical drivers such as waves, sea-level rise, water-level variability, and other terrestrial and oceanographic processes.

To simulate future shoreline evolution, many well-tested numerical models have emerged, generally falling under two categories of (1) physics-based models (e.g., Delft3D – Lesser et al., 2004) and (2) process-based (reduced-physics) models (e.g., CoSMoS-COAST – Vitousek et al., 2017, 2022b, and LX-Shore – Robinet et al., 2018). Physics-based models, while proven to deliver robust results for event-driven (short time scale) and spatial extents of several km simulations (Roelvink et al., 2009), are generally inappropriate for simulating long-term (decades) and large-scale (> 10s of km) shoreline evolution due to their prohibitive computational costs and significant error/uncertainty build-up (Robinet et al., 2018; French et al., 2016). Thus, the growing need for long-term and large-scale predictions of shoreline change has led to the development and application of data-driven, process-based models, which have demonstrated considerable skill across a wide range of spatiotemporal scales and coastal environments, while incorporating the major processes contributing to shoreline evolution.

The focus region of this study, the US Pacific Northwest (PNW), is projected to experience greater levels of coastal hazards due to projected sea-level variability, changing storminess patterns, and potential changes in the frequency and intensity of El Niño events. Many PNW communities, such as Tillamook County, Oregon, have recently been experiencing higher shoreline change rates (SCRs) compared to historical SCRs (Ruggiero, 2013; Anderson et al., 2018). For example, the percentage of the Oregon coastline experiencing modern (2002-2016) erosion rates > 1 m/yr compared to the long-term (1967-2002) has risen from 18% to 42% (Light, 2021). The increase of erosional behavior in recent SCRs emphasizes the need for robust multiscale projections of future SCRs while accounting for the uncertainties in climate forcing, such as wave and sea-level variability, as well as adaptation measures enacted by coastal communities.

The current work represents a starting point in our effort to predict long-term, large-scale shoreline evolution across the entire PNW. Here, we focus on modeling shoreline change in Tillamook County, Oregon. To this end, we take advantage of both field data collection campaigns and a recently updated process-based model, called CoSMoS-COAST, that incorporates components of short- and long-term shoreline change processes, e.g., cross-shore and longshore sediment transport. First, we calibrate the model by assimilating the historical shoreline observations (during 1997-2016), and then, we assess the model's performance in hindcasting observed shoreline positions during the validation period (2016-2021). Ultimately, we evaluate the recent (2016-2021) SCRs throughout the county's coastline and compare them to the short-term/modern (2002-2016) SCRs. Our findings will inform on the suitability of CoSMoS-COAST, as a data-driven, process-based model, to be employed for the multiscale projection of shoreline evolution in Tillamook County, Oregon, and eventually, for the entire PNW under a broad range of climatic and anthropogenic coastal management scenarios.

Study Site

Tillamook County, located in northwestern Oregon, is home to ~100 km of the state's coastline and offers many recreational, ecological, and aesthetic features that the PNW beaches typically provide. This region features a broad variety of coastal geomorphology, e.g., sandy beaches (dune-backed and riprap revetment-backed; covering ~63% of the county's coastline), bluff-backed beaches, cobble and boulder beaches, and cliffs. Tillamook County, among other coastal communities in the PNW, is currently experiencing heightened levels of coastal issues including coastal flooding and erosion at some locations (Ruggiero et al., 2013; Lipiec et al., 2018; Mills et al., 2018). While ~65% of the county's coastline is eroding, this erosional trend is anticipated to intensify under various physical drivers such as the climate change-induced sea-level rise and possible changes in storminess patterns (Ruggiero, 2013; Light, 2021), posing several threats to this coastal environment.

Data and Methods

CoSMoS-COAST Governing Equation and Features

The model used here, CoSMoS-COAST (Vitousek et al., 2017, 2022b), is a "one-line" shoreline evolution model that integrates various short- and long-term processes contributing to shoreline change. The model's main governing equation evaluates the variation of shoreline position (Y) over time (t) on each transect (discussed below in the "Spatial Discretization" section) and is given by

$$\frac{\partial Y}{\partial t} = \overbrace{\underbrace{-\frac{1}{d_c}\frac{\partial Q}{\partial X}}_{\substack{[1]\ longshore\\ transport}} - \underbrace{\frac{c}{\tan\beta}\frac{\partial S}{\partial t}}_{\substack{[2]\ shoreline\\ migration\\ due\ to\\ sea-level\ rise}} + \underbrace{v_{lt}}_{\substack{[3]\ long-term\\ shoreline\ trend;\\ unresolved\ processes}}}^{long-term\ processes}$$

$$+ \overbrace{\underbrace{\frac{1}{\tau}\left(Y_{eq} - Y\right)}_{\substack{[4]\ cross-shore\\ "equilibrium"\\ transport}} + \underbrace{\varepsilon}_{\substack{[5]\ additive\\ noise}}}^{short-term\ processes}. \quad (1)$$

Term [1] in Eq. (1) incorporates the contribution of longshore sediment transport, where d_c is the depth of closure, Q is the longshore sediment transport rate, and X represents the alongshore (parallel to the local shoreline) coordinate. Term [2] represents the shoreline recession due to sea-level rise, known as the "Bruun rule", where $\tan\beta$ is the active beach profile average slope, S is the magnitude of sea-level rise, and c is a calibration coefficient. Term [3], defined as the long-term shoreline trend, represents residual long-term sediment transport processes, e.g., fluvial sources and sinks of sediment, which are not contained in terms [1] and [2]. Term [4] models the wave-driven, cross-shore sediment transport occurring on a short-term/seasonal basis where Y_{eq} and τ are the equilibrium shoreline position and equilibrium time scale. Lastly, term [5] aims to estimate the parametric uncertainty in the model (see Vitousek et al., 2017, 2022b for more details on Eq. (1)).

CoSMoS-COAST is equipped with an *Ensemble Kalman Filter (EnKF)* data assimilation method (with 1,000 ensemble members) which enables it to nudge the model solution and model parameters to best fit the observed data during the calibration (training) period. In other words, as the model assimilates historical shoreline positions during the simulation process, it calibrates multiple coefficients/variables in Eq. (1), such as v_{lt} in term [3], adjusting the model's performance in hindcasting the historical shoreline positions, which lends higher confidence in the model's ability to predict future shoreline evolution. Furthermore, the recent "localization" feature available in the data assimilation method enables transects with many observed historical shoreline positions (i.e., data-rich transects) to influence/adjust the model solution and parameters on adjacent transects with limited observed historical shoreline positions (i.e., data-poor transects) (see Appendix B in Vitousek et al., 2022b for more details on data assimilation).

Spatial Discretization

Tillamook County's coastline is discretized into shore-perpendicular transects spaced every 50 m in the alongshore direction (X), representing the model "grid". To produce these transects, we digitized a "reference shoreline", as a visually identifiable shoreline, from the latest high-resolution satellite imagery available on Google Earth Pro (https://www.google.com/earth/versions), as well as a "non-erodible shoreline" located on the onshore side of the reference shoreline (following the method described in Vitousek et al., 2017). The non-erodible shoreline represents the furthest-onshore extent of beaches that are typically constrained by dunes, vegetation, cliffs, bluffs, or urban development. As shown in Figure 1, transects are straight lines extending from the non-erodible shoreline as their onshore limit to an offshore point while perpendicular to the reference shoreline. We also labeled groups of model transects into so-called "littoral cells", i.e., sedimentologically isolated stretches, along Tillamook County's coastline: (1) Rockaway, (2) Netarts, (3) Sand Lake, and (4) Neskowin, which are separated via distinguished headlands along the coastline. Transect-based discretization in CoSMoS-COAST allows for covering long, irregular coastlines, where these transects act as "rails", along which the shoreline position can evolve through time.

CoSMoS-COAST is capable of predicting shoreline evolution for different coastal settings (i.e., different beach types) by incorporating relevant terms among terms [1]-[4] in Eq. (1). Shoreline evolution in long, sandy beaches is performed via the "full-model" version of Eq. (1), i.e., all terms in Eq. (1) contribute to the shoreline evolution (transects designated as "full-model" are shown in green in Figure 1). On the other hand, in short, sandy beaches ("pocket beaches"), long-term alongshore sediment transport is negligible and term [1] is omitted (these transects are specified as "cross-shore only" and are depicted in yellow in Figure 1). In the case of cobble or heterogeneous sandy/rocky beaches, longshore and cross-shore sediment transport assumptions (terms [1] and [4]) are not valid anymore and these terms are ignored (transects specified as "rate only" and represented in red in Figure 1). Finally, no predictions for shoreline evolution are carried out for the coastal settings not discussed above, e.g., sea cliffs and rocky shorelines, and their associated transects are labeled as "no prediction" (depicted in purple in Figure 1). Among the 1,678 transects defined for this study region (numbered from south to north), "full model", "cross-shore only", "rate only", and "no prediction" types are assigned to 76%, 1%, 4.5%, and 18.5% of the transects, respectively.

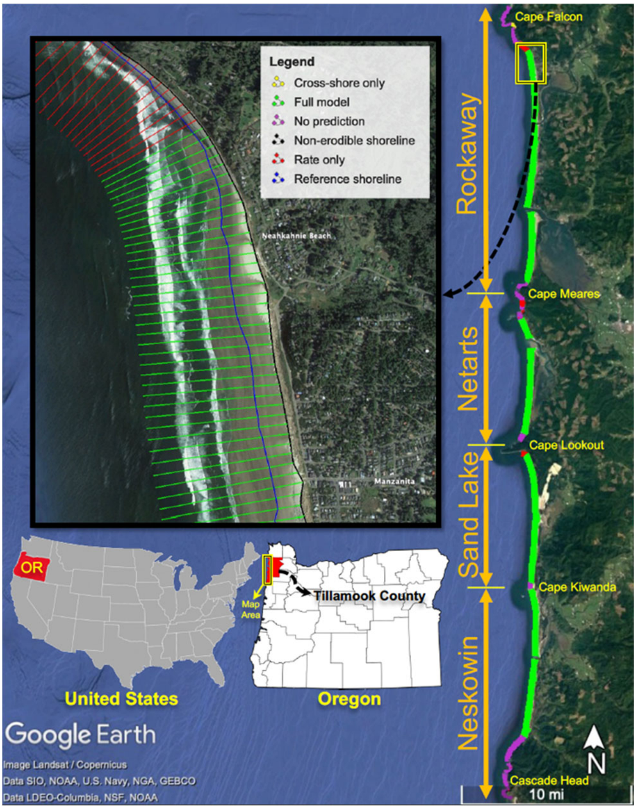

Fig. 1. 50-m spaced transects and their types along Tillamook County's four littoral cells used in CoSMoS-COAST. Base maps from Google Earth Pro.

Wave Forcing

Longshore and cross-shore sediment transport processes are driven by the interaction of waves, shoreline orientation, and profile elevation, respectively, over various time scales. Thus, waves play an integral role in the prediction of shoreline evolution, which here are simulated via terms [1] and [4] in Eq. (1). To evaluate these terms at any time, the time series of bulk parameter wave triplets, i.e., (1) significant wave height, (2) peak wave period, and (3) incident wave direction, are required for the simulation period. Here, we utilized CSIRO's hindcasted wave time series (available for 1979-present; Durrant et al., 2019) at the closest offshore, deep-water location (node) to Tillamook County. Since the littoral cells along Tillamook County's coastline are relatively long [O(10s of km)], we needed to account for the alongshore nonuniformity of the wave conditions. We downscaled (propagated) the deep-water wave time series to alongshore varying (~100 m spatial resolution along the coastline) 20 m depth contour conditions, which is very close to the offshore end of each individual model transect. This propagation was carried out via previously developed look-up tables as a surrogate for SWAN model (Allan et al., 2015; Booij et al., 1999), which implements shoaling and refraction during wave propagation. Then, the daily average of the wave triplets time series is used to hindcast shoreline positions via CoSMoS-COAST, which applies a daily model time step.

Historical Shoreline Positions

Historical shoreline positions are essential for the calibration and validation of CoSMoS-COAST model, as with any other numerical shoreline change model. In this study, historical shoreline positions are extracted from two sources. The first source, airborne LIDAR data, has provided us with three data sets, all of which fully cover Tillamook County's coastline (Light, 2021), collected in ~September 2002, ~June 2011, and ~May 2016, by NASA/USGS, USACE, and USGS, respectively. The second source is the seasonal topographic GPS profile surveys, available at many discrete locations along Tillamook County's coastline (Allan & Hart, 2008). This data set is spatially relatively sparse (~1 km spacing) but provides seasonal (~3-month temporal resolution) observations at the majority of the locations where the profile surveys are carried out, not covering Sand Lake only among the four littoral cells. Satellite imagery-derived historical shoreline positions, as another potential source, have emerged to be a game-changer in the calibration and validation efforts in shoreline evolution modeling (Vos et al., 2019; Vitousek et al., 2022a, b), although not incorporated in our study at this time.

Model Performance Assessment

Assessment of model performance is heavily influenced by the quantity of the available observed data (historical shoreline positions in our case). We rely on the GPS- and LIDAR-derived historical shoreline positions during the validation period (2016-2021) to quantify the performance of CoSMoS-COAST model. The metric utilized here is the Root-Mean-Square-Error (RMSE), which is defined as

$$RMSE = \sqrt{\overline{(Y_{obs} - Y_{mod})^2}}\,, \tag{2}$$

where Y_{obs} and Y_{mod} are the observed and modeled shoreline positions, respectively, during the validation period, and the overbar is the average over time.

Results

Using the CoSMoS-COAST model, we hindcasted the shoreline positions along all littoral cells on Tillamook County's coastline for the calibration (Jan 1, 1997 to Mar 31, 2016) and the validation (Apr 1, 2016 to Dec 31, 2020) periods using the hindcasted wave time series and a sea-level rise scenario that results in 0.8 m of rise by 2100 (i.e., the Intermediate scenario for PNW (Sweet et al., 2022)). The model results are based on an ensemble of 1,000 simulations to account for the model's epistemic/parametric uncertainties. Figure 2 represents the wave heights (Panel A) and hindcasted shoreline positions (Panel B) for the simulation period at one of the transects (#1309) with a comparatively large number of available/observed historical shoreline positions along Rockaway littoral cell. By comparing these two panels, it is evident the model satisfactorily captures the influence of the seasonal variability in the wave climate, where the low wave energy during summer (high wave energy during winter) causes the shoreline position to prograde (recede). This relationship between wave energy and shoreline position is distinctly obvious during Winter 2016 when the significantly heightened wave energy during the 2015/2016 El Niño season (Barnard et al., 2017) caused a sizeable recession of shoreline position. Moreover, as the model assimilates more historical shoreline positions through time, the uncertainty of the modeled shoreline positions (the width of the uncertainty bands in Figure 2B) tends to decrease considerably, where data-rich periods constrain model uncertainty and vice versa. We also calculated the modeled SCRs (via linear regression) during the validation period at all transects (see the thick red line in Figure 2) to compare with the modern (2002-2016) SCRs, as discussed below.

To assess the performance of the model in recreating historical shoreline positions, we estimated the RMSE between the modeled and observed shoreline positions via Eq. (2) during the validation period at all transects, represented in Figure 3B (note that the star symbol in this figure represents transect #1309, which is used in Figure 2, and the black dashed lines depict the latitudinal limits of littoral cells, as well as in the following figures). A visual pattern can be detected by examining the variation range of the RMSE values for different littoral cells and comparing it to the number of total observed historical shoreline positions (N_{obs}) during the hindcast period at transects present in these littoral cells (Figure 3A). To uncover this pattern, we divided Tillamook County's coastline into three regions (1) Rockaway (shaded blue in Figure 2B), (2) Netarts and Sand Lake (shaded green in Figure 2B), and (3) Neskowin (shaded red in Figure 2B). We found the standard deviation of the RMSE values (σ_{RMSE}) for all transects (only transects with $N_{obs} \geq 4$) in regions 1 to 3 to be ~6.3 m (~1.5 m), ~9.8 m (~14.3 m), and ~9.1 m (~2.6 m), where the average of N_{obs} is ~4.3 (~62), ~2.6 (~9), and ~3.6 (~47), respectively. This notable inverse correlation between σ_{RMSE}

and N_{obs} throughout these three regions is mainly due to the localization effect embedded in the data assimilation technique in CoSMoS-COAST, where data-rich ($N_{obs} \geq 45$) transects assist in the assimilation of the adjacent data-poor ($N_{obs} \leq 3$) transects to optimally infer model parameters during the calibration period.

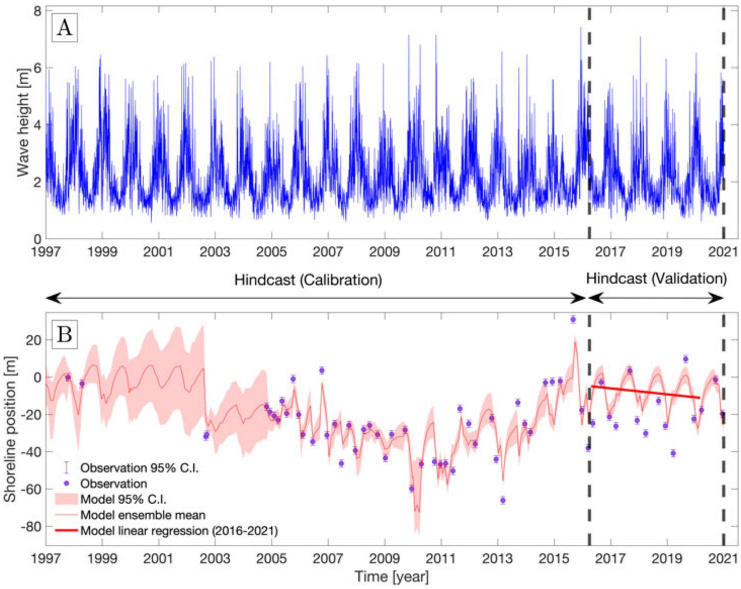

Fig. 2. (A) Wave forcing, and (B) observed and modeled shoreline positions during the hindcast period at transect #1309 (located in Rockaway littoral cell).

We estimated the average of RMSE across all data-rich ($N_{obs} \geq 45$) transects (shown in orange in Figure 3B) as ~9.2 m, which is comparable to the range of RMSE values for well-calibrated process-based shoreline evolution models (~5-8 m; Montaño et al., 2020). Note that in Figure 3B we find a sizable difference in RMSE values as a function of the total number of observations (N_{obs}) for several transects in Rockaway and Neskowin littoral cells and the rest of the transects. For many transects, GPS-derived survey data is unavailable, and the only source of observed data is the spatially continuous, yet temporally sparse LIDAR-derived shoreline data which fully covers all littoral cells. The transects with significantly low/high RMSE values are mainly associated with $N_{obs} \leq 3$, where only one of these data points (extracted from the 2016 LIDAR data set) lies within the validation period and is used in the calculation of RMSE, being insufficient to objectively assess the model's performance at these transects. Hence, using only one shoreline data point for model validation at certain transects in some cases fortuitously results in low RMSE values, and, in other cases, unluckily results in high RMSE values. It is worth mentioning that the transects located in close proximity to river/bay entrances (dashed red lines in Figure 3B) generally report the highest RMSE values. This can be due to unresolved processes (e.g., fluvial sources and sinks) not explicitly integrated into the model's governing equations.

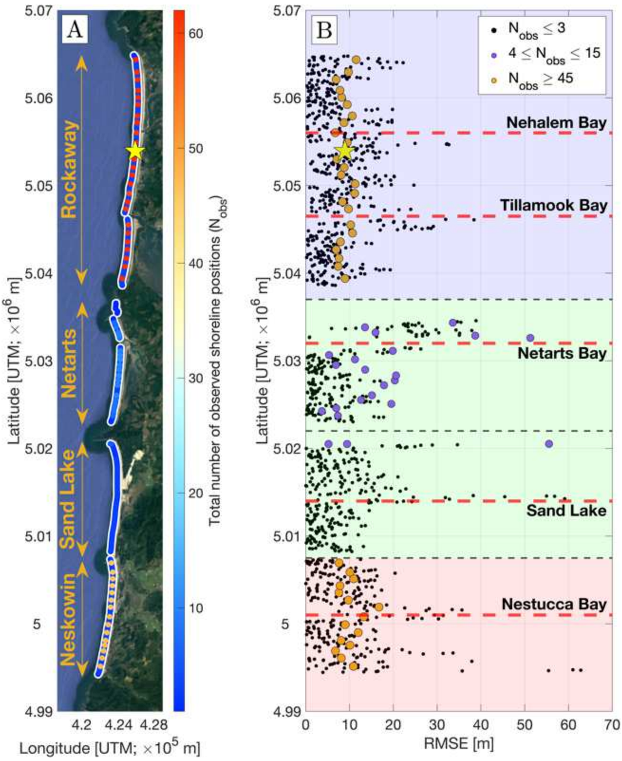

Fig. 3. (A) The total number of observed historical shoreline positions and (B) the RMSE values during the validation (2016-2021) period at all transects. Base maps are from Google Earth Pro.

Finally, we exploited the modeled shoreline positions during the validation period to evaluate the interannual trend in shoreline positions (shoreline change rate (SCR)) at all transects via linear regression (e.g., see the thick red line in Figure 2B). This allows us to compare the modeled recent (2016-2021) SCRs to available modern SCRs (2002-2016 observed endpoint rates; from Light, 2021), as depicted in Figure 4A, where SCR values between –0.25 m/yr and 0.25 m/yr are designated as "stable" (green shaded area in Figure 4A), < –0.25 m/yr as "erosional" (red shaded area in Figure 4A), and > 0.25 m/yr as "accretional" (blue shaded area in Figure 4A), respectively.

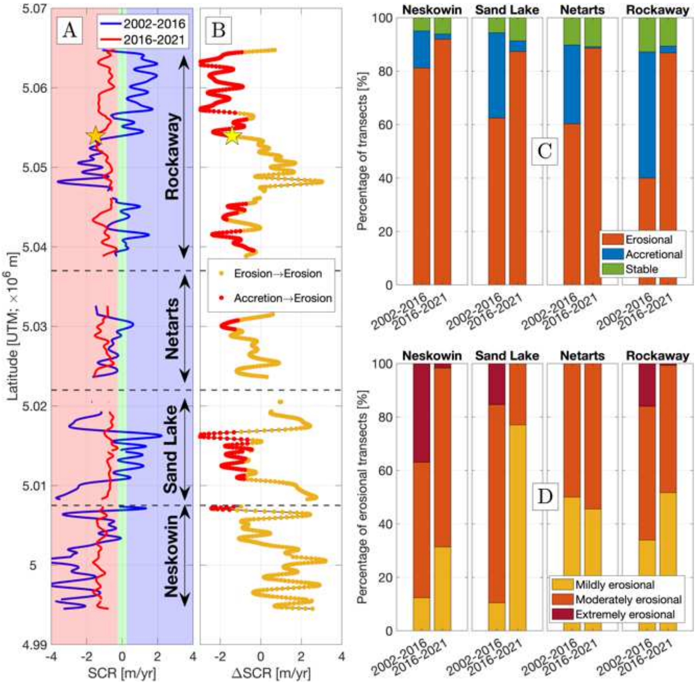

Fig. 4. (A) SCRs, (B) change in SCRs and regimes, (C) the percentage of transects in each SCR regime, and (D) the percentage of erosional transects in each erosional regime during each period.

The difference between the observed 2002-2016 shoreline trend and the model-predicted 2016-2021 trend ($SCR_{2016-2021} - SCR_{2002-2016}$; shown in Figure 4B) highlights that at the majority of the transects (specifically in Netarts and Neskowin littoral cells) the erosional behavior persists, while at a smaller fraction of transects the older accretional regimes shift to erosional (especially in Rockaway and Sand Lake littoral cells). Note that the curves in Figures 4A and 4B are low-pass-filtered for better representation of alongshore variability. Only at a negligible fraction of transects does the regime shift from erosional to accretional, similar to the persistence of accretional behavior. Figure 4C represents the percentage of transects in different regimes during the 2002-2016 and 2016-2021 periods at all littoral cells, where a prevailing increase in erosional transects is estimated. This underscores the emergence of a growing erosional trend on Tillamook County's coastline. To assess the severity of this trend, we categorized the erosional SCRs into three different erosional regimes: (1) mildly erosional (–1 m/yr < SCR < –0.25 m/yr), (2) moderately erosional (–3 m/yr < SCR < –1 m/yr), and (3) extremely erosional (SCR < –3 m/yr). The percentage of erosional transects lying in each of these erosional regimes is shown in Figure 4D, pointing out that from 2002-2016 to 2016-2021 the severity of erosional behavior across all littoral cells (except Netarts) is alleviated, yet almost all of the transects shifting from accretional to erosional regime end up in the mildly erosional regime. This highlights that almost no extreme erosional behavior was estimated in any of the littoral cells during 2016-2021 despite the overall increase in erosional behavior.

Discussion and Conclusions

In this study, we calibrated and validated a process-based, one-line shoreline evolution model, CoSMoS-COAST, which incorporates multiple short- and long-term components of multiscale shoreline evolution. We found that the model's performance is strongly correlated with the number of observed shoreline positions during the calibration period. This emphasizes the importance of the data quantity (i.e., the number of observed shoreline positions) in the application of data-driven, process-based models, justifying the applicability of these models to data-rich regions. Fortunately, the growing availability of satellite imagery-derived shoreline positions can potentially enable the use of process-based models for the projections of shoreline evolution globally, especially in historically data-poor regions (Vos et al., 2019; Vitousek et al., 2022a). Additionally, we identified an extensive increase in SCRs exhibiting erosion throughout Tillamook County's coastline during the 2016-2021 period compared to the 2002-2016 period, where a higher fraction of transects exhibits erosional behavior. However, the intensity of this new erosional behavior has been suppressed and considerably less extreme erosion is detected during 2016-2021. Also, the SCRs during this period represent a lack of significant alongshore variability. We hypothesize the approximately alongshore-uniform erosional SCRs are driven partially by sea-level rise-induced ("Bruunian") change in shoreline positions (since here we focus on the recent shoreline trends rather than long-term projections, sea-level rise-induced erosion is anticipated to be relatively minor) but mainly forced by the cross-shore sediment transport processes driven by increasing wave-energy flux during winters 2019 and 2020 compared to winters 2017 and 2018. To test this hypothesis, we calculated the 2016-2021 SCRs by ignoring cross-shore sediment transport and sea-level rise-induced shoreline position changes (terms [2] and [4] in Eq. (1)) and found that for almost all transects, 2016-2021 SCRs fall within the stable region (results not shown here). This behavior is expected since by ignoring terms [2] and [4] in Eq. (1), the only main remaining process is the gradients in longshore sediment transport (term [1] in Eq. (1)), which as a process that usually becomes more important over longer time scales, it does not influence the shoreline positions drastically over the short span of time allocated (~4.5 years).

So far CoSMoS-COAST has performed satisfactorily with the spatially sparse supply of quality historical shoreline positions in our application. Moreover, this model resolves various components (e.g., short- and long-term processes) in the shoreline change sufficiently. In our next step of the current study, we will incorporate satellite imagery-derived historical shoreline positions (CoastSat – Vos et al., 2019) into our model, which will provide us with spatiotemporally high-resolution data for the whole hindcasting duration. Consequently, the potential increase in the model's skill will lend confidence in its capability to predict future (e.g., 2021-2100) shoreline evolution in Tillamook County under several projected climatic and management/anthropogenic scenarios. This study represents a starting point in the long-term projection of shoreline evolution throughout the entire PNW (Oregon and Washington) coastline since Tillamook County features the majority of the coastal settings present in other coastal regions in the PNW. Ultimately, this long-term, large-scale projection will help to inform on the risks associated with future shoreline evolution and assist coastal management entities in the design and implementation of efficient adaptation strategies to cope with these risks over various time scales.

Acknowledgments

This work is funded by NOAA via the NOS/NCCOS/CRP Effects of Sea-Level Rise (ESLR) Program (grant no. NA19NOS4780180) and the Coastlines and People program of the National Science Foundation under cooperative agreement 2103713. We also thank Jacob Light and Rajasree Bharathan Radhamma for providing us with Tillamook County's historical shoreline change rates and coastal morphometric data sets.

References

Allan, J. C. & Hart, R. (2008). Oregon beach and shoreline mapping and analysis program: 2007-2008 beach monitoring report: Oregon Department of Geology and Mineral Industries, Open file report O-08-15.

Allan, J. C., Ruggiero, P., Garcia-Medina, G., O'Brien, F., Stimely, L. & Roberts, J. (2015). Coastal flood hazard study, Tillamook County Oregon. Special Paper 47, Oregon Department of Geology and Mineral Industries.

Anderson, D., Ruggiero, P., Antolínez, J. A., Méndez, F. J. & Allan, J. (2018). A climate index optimized for longshore sediment transport reveals interannual and multidecadal littoral cell rotations. *Journal of Geophysical Research: Earth Surface, 123*(8), 1958-1981.

Barnard, P. L., Hoover, D., Hubbard, D. M., Snyder, A., Ludka, B. C., Allan, J. & Serafin, K. A. (2017). Extreme oceanographic forcing and coastal response due to the 2015–2016 El Niño. *Nature Communications*, *8*(1), 1-8.

Booij, N. R. R. C., Ris, R. C. & Holthuijsen, L. H. (1999). A third-generation wave model for coastal regions: 1. Model description and validation. *Journal of Geophysical Research: Oceans, 104*(C4), 7649-7666.

Durrant, T., Hemer, M., Smith, G., Trenham, C. & Greenslade, D. (2019). CAWCR Wave Hindcast - Aggregated Collection. v5. CSIRO. Service Collection. http://hdl.handle.net/102.100.100/137152?index=1.

French, J., Payo, A., Murray, B., Orford, J., Eliot, M. & Cowell, P. (2016). Appropriate complexity for the prediction of coastal and estuarine geomorphic behaviour at decadal to centennial scales. *Geomorphology*, *256*, 3-16.

Lesser, G. R., Roelvink, J. V., van Kester, J. T. M. & Stelling, G. S. (2004). Development and validation of a three-dimensional morphological model. Coastal engineering, 51(8-9), 883-915.

Light, J. W. (2021). Morphodynamic Evolution of Coastal Oregon: Using New Lidar-derived Beach and Sand Dune Morphometrics to Explore Multi-decadal Change.

Lipiec, E., Ruggiero, P., Mills, A., Serafin, K. A., Bolte, J., Corcoran, P. & Lach, D. (2018). Mapping out climate change: assessing how coastal communities adapt using alternative future scenarios. *Journal of Coastal Research*, 34(5), 1196-1208.

Mills, A. K., Bolte, J. P., Ruggiero, P., Serafin, K. A., Lipiec, E., Corcoran, P. & Lach, D. (2018). Exploring the impacts of climate and policy changes on coastal community resilience: Simulating alternative future scenarios. *Environmental Modelling & Software*, *109*, 80-92.

Montaño, J., Coco, G., Antolínez, J. A., Beuzen, T., Bryan, K. R., Cagigal, L. & Vos, K. (2020). Blind testing of shoreline evolution models. *Scientific Reports*, *10*(1), 1-10.

Nicholls, R. J., French, J. R. & van Maanen, B. (2016). Simulating decadal coastal morphodynamics. *Geomorphology*, 1-2.

Robinet, A., Idier, D., Castelle, B. & Marieu, V. (2018). A reduced-complexity shoreline change model combining longshore and cross-shore processes: The LX-Shore model. *Environmental Modelling & Software*, *109*, 1-16.

Roelvink, D., Reniers, A., Van Dongeren, A. P., De Vries, J. V. T., McCall, R. & Lescinski, J. (2009). Modelling storm impacts on beaches, dunes and barrier islands. *Coastal Engineering*, *56*(11-12), 1133-1152.

Ruggiero, P. (2013). Is the intensifying wave climate of the US Pacific Northwest increasing flooding and erosion risk faster than sea-level rise?. *Journal of Waterway, Port, Coastal, and Ocean Engineering, 139*(2), 88-97.

Ruggiero, P., Kratzmann, M. G., Himmelstoss, E. A., Reid, D., Allan, J. & Kaminsky, G. (2013). National assessment of shoreline change: historical shoreline change along the Pacific Northwest coast. US Geological Survey.

Sweet, W. V., Hamlington, B. D., Kopp, R. E., Weaver, C. P., Barnard, P. L., Bekaert, D. & Zuzak, C. (2022). Global and regional sea level rise scenarios for the United States: Updated mean projections and extreme water level probabilities along US coastlines (No. 01). NOAA Technical Report.

Vitousek, S., Barnard, P. L., Limber, P., Erikson, L. & Cole, B. (2017). A model integrating longshore and cross-shore processes for predicting long-term shoreline response to climate change. *Journal of Geophysical Research: Earth Surface*, *122*(4), 782-806.

Vitousek, S., Buscombe, D., Vos, K., Barnard, P. L., Ritchie, A. & Warrick, J. (2022a). The future of coastal monitoring through satellite remote sensing. *Cambridge Prisms: Coastal Futures*, 1-43.

Vitousek, S., Vos, K., Splinter, K. D., Erikson, L. & Barnard, P. L. (2022b). A model integrating satellite-derived shoreline observations for predicting fine-scale shoreline response to waves and sea-level rise across large coastal regions. *Manuscript submitted for publication.*

Vos, K., Splinter, K. D., Harley, M. D., Simmons, J. A. & Turner, I. L. (2019). CoastSat: A Google Earth Engine-enabled Python toolkit to extract shorelines from publicly available satellite imagery. *Environmental Modelling & Software*, *122*, 104528.