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Key Points:
- Sea level rise threatens the very existence of natural beaches throughout the world
- Beaches will increasingly become engineered systems through sand renourishment and the construction of seawalls
- The predictive capability of coastal evolution models must improve significantly in order to meet the challenges of changing climate

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Can beaches survive climate change?

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Abstract Anthropogenic climate change is driving sea level rise, leading to numerous impacts on the coastal zone, such as increased coastal flooding, beach erosion, cliff failure, saltwater intrusion in aquifers, and groundwater inundation. Many beaches around the world are currently experiencing chronic erosion as a result of gradual, present-day rates of sea level rise (about 3 mm/year) and human-driven restrictions in sand supply (e.g., harbor dredging and river damming). Accelerated sea level rise threatens to worsen coastal erosion and challenge the very existence of natural beaches throughout the world. Understanding and predicting the rates of sea level rise and coastal erosion depends on integrating data on natural systems with computer simulations. Although many computer modeling approaches are available to simulate shoreline change, few are capable of making reliable long-term predictions needed for full adaption or to enhance resilience. Recent advancements have allowed convincing decadal to centennial-scale predictions of shoreline evolution. For example, along 500 km of the Southern California coast, a new model featuring data assimilation predicts that up to 67% of beaches may completely erode by 2100 without large-scale human interventions. In spite of recent advancements, coastal evolution models must continue to improve in their theoretical framework, quantification of accuracy and uncertainty, computational efficiency, predictive capability, and integration with observed data, in order to meet the scientific and engineering challenges produced by a changing climate.

1. Introduction

How do beaches respond to climate change? Reliable, quantitative answers to this question are increasingly sought for adaptation and mitigation planning as rates of sea level rise continue to accelerate [*Ranasinghe and Stive*, 2009; *Nicholls et al.*, 2016; *Ranasinghe*, 2016]. The answer to this question is notoriously difficult to obtain because it lies at the intersection of ocean, earth, and atmospheric science, civil engineering, and policy.

Coastlines evolve in response to oceanographic and geologic processes on a wide range of spatial and temporal scales. These processes include (1) sea level rise; (2) tides and currents; (3) storm magnitude, frequency, direction, and duration; (4) climatic cycles like El Niño; (5) sand supply from rivers and reefs; and (6) tectonic processes causing uplift or subsidence of coasts, among many others (Figure 1). Among these processes, sea level rise represents a clear and present threat to the very existence of many beaches, especially in urban environments where landward migration is inhibited by infrastructure. Beaches are getting squeezed between a rising ocean and the landward hardscape, effectively being drowned by sea level rise. This is where beaches are important because they provide storm protection for the 1 billion people who will live in the coastal zone by the end of the 21st century [*Neumann et al.*, 2015]. Similarly, freshwater resources in coastal aquifers are getting squeezed between rising seawater levels and the urban land surface [*Michael et al.*, 2017].

Global average sea level has risen more than 0.2 m in the past 100 years [*Church and White*, 2011] and is projected to rise another 0.3 to 2.0 m or even more by 2100 [*Horton et al.*, 2014; *Kopp et al.*, 2014]. The current rate of rise is expected to accelerate as the melting of land-based ice sheets increases in response to global warming, which is concentrated in polar regions [*DeConto and Pollard*, 2016]. Further, given current carbon emission trajectories, we may now be committed to at least 9 m of sea level rise over the coming centuries [*Clark et al.*, 2016].

For many coastal regions, particularly those with limited sediment supply, sea level rise therefore is or will become the primary driver of chronic coastal change [*FitzGerald et al.*, 2008; *Walkden and Dickson*, 2008, *Jones et al.*, 2009, *Anderson et al.*, 2015, *Hurst et al.*, 2016]. Although both the magnitude of future sea level rise and the magnitude of consequent shoreline change remain open questions, the basic behavior of future shoreline change due to sea level rise alone is well understood: shorelines retreat. However, the details related to any individual beach matter greatly for assessing the best options for mitigation or adaptation.

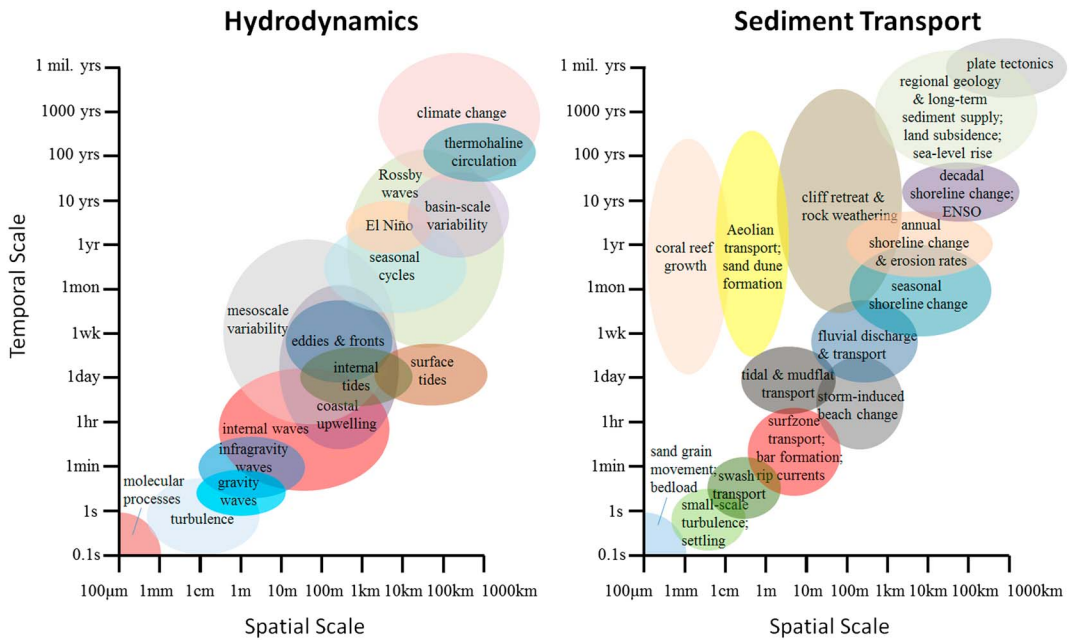

Figure 1. The multiscale nature of (left) hydrodynamics and (right) sediment transport. Hydrodynamic processes adapted from *Chelton* [2001].

Quantitative model predictions of shoreline change generally must account for the following processes, depending on the time and spatial scales of interest: (a) wave- and current-driven alongshore transport (e.g., transport that causes sand to accumulate on one side of jetties); (b) wave- and current-driven cross-shore transport (i.e., transport perpendicular to shore, e.g., the formation of offshore sandbars); (c) aeolian transport (e.g., the formation of sand dunes) and dune erosion; (d) natural and anthropogenic (changes in) sediment supply; (e) coastal cliff erosion, if cliffs are present; and (f) the interaction of these processes with coastal infrastructure.

Beaches, which can include adjacent dunes, marshes, or other ecosystems, support tremendous economic activity and serve as "natural" flood protection for adjacent communities. As a result, many beaches are artificially maintained through engineering (e.g., beach nourishment, building of seawalls, groins, and berms) and can no longer be considered natural systems [*Flick*, 1993]. Increased coastal development on chronically eroding shorelines often causes the transition from natural to engineered systems, in order to preserve beaches and the benefits they provide [*Armstrong et al.*, 2016]. However, it is the act of engineering our shorelines that may doom them in the long run. Beaches can survive by migrating landward; however, this is no longer possible without moving entire cities or, alternatively, by adding massive amounts of sand to the system to keep beaches in place. Quantitative model predictions of shoreline evolution are needed to guide coastal policy that will enable communities to either maintain the natural beach system or facilitate its transition to an engineered system [*Lazarus et al.*, 2016], or even lead to a decision to abandon coastal development. Because adaptation strategies can take years to implement, predictions of shoreline behavior on the scale of decades (and longer) are increasingly important.

Through many studies of beaches and general modeling efforts we have a good understanding of the overall processes and dynamics affecting the evolution of beaches. Accurate modeling needed to predict the long-term behavior of specific coastal systems, however, requires integrating models with extensive local historical data and expanding shoreline monitoring efforts going forward.

2. Integrating Data and Models

Many different models exist to predict coastal evolution. However, all inevitably rely upon approximations of complex, multiscale systems and thus are subject to error. Sediment-transport models, in particular, often

lack well-defined governing equations, that is, equations that describe how the unknown variables, such as sediment volume, will change. Instead, sediment-transport models rely heavily on combining the results of numerous experimentally derived equations that describe small-scale simplified representations of important processes, such as the motion of individual sand grains in turbulent flow. In spite of these approximations, models can be useful tools to explain and estimate beach change, especially when thoughtfully integrated with observations.

Three common approaches to sediment-transport modeling are "physics-based," "process-based," and "data-based" (or "empirical") models. Physics-based models numerically solve governing equations (e.g., conservation of mass, momentum, and sediment) for hydrodynamics (e.g., the effects of tides and currents), waves, sediment transport, and morphology. Examples are Delft3D [*Roelvink and Van Banning*, 1995], XBeach [*Roelvink et al.*, 2010], Mike21 [*Warren and Bach*, 1992; *Kaergaard and Fredsoe*, 2013], and the Regional Ocean Modeling System [*Warner et al.*, 2010]. Process-based models typically account for a single dominant physical process, e.g., beach profile adjustment due to sea level rise [*Bruun*, 1962], wave-driven cross-shore shoreline change [*Miller and Dean*, 2004; *Yates et al.*, 2009, 2011; *Davidson et al.*, 2010, 2013; *Splinter et al.*, 2013, 2014], and alongshore sediment transport [*Pelnard-Considere*, 1956; *Larson et al.*, 1997; *Ashton et al.*, 2001; *Ashton and Murray*, 2006]. Data-based or empirical models predict shoreline change from previously observed behavior. For example, historical shoreline analyses [*Dolan et al.*, 1978; *Crowell et al.*, 1991; *Thieler and Danforth*, 1994; *Fletcher et al.*, 2003] derive rates of shoreline change from aerial photographs and then extrapolate historical trends. Although simple extrapolations of shoreline position break down in a changing climate, advanced data-based models (e.g., Bayesian networks) may represent a viable option for prediction [*Plant et al.*, 2016].

Physics-based simulations generally represent the most robust approach (at least in theory), yet they are often prohibitively expensive in computational cost and do not necessarily provide more reliable results than simplified models [*Murray*, 2007; *Ranasinghe et al.*, 2013; *French et al.*, 2016]. The sediment-transport modeler's ultimate goal is the accurate "side-by-side" comparison of model simulation results and field data, but good agreement is rare, particularly for large spatial and temporal scales. Much of coastal zone's unpredictability stems from its inherent geologic variability (e.g., sediment types, sizes, sources, and sinks) and the model's reliance on sediment transport equations developed from laboratory or field experiments. Furthermore, it becomes difficult and time-consuming to choose parameters that represent small-scale variability within the system of interest and write, calibrate, and validate equations that describe their interactions.

Recently, scientists have developed hybrid shoreline-change models [*van Maanen et al.*, 2016, *Vitousek et al.*, 2017], in which, for example, (1) the wave dynamics are simulated by using a physics-based approach, (2) a synthesis of process-based models is used to forecast shoreline evolution, and (3) historical data are used to improve estimates of the model's parameters [e.g., *Long and Plant*, 2012]. The hybrid approach leverages the multiple advantages offered by different modeling approaches. For example, applying physics-based models of wave dynamics (e.g., Simulating Waves Nearshore [*Booij et al.*, 1999]) often provides vastly superior results for nearshore wave heights, periods, and directions. By combining process-based models (e.g., models for alongshore or cross-shore sediment transport), the synthesized hybrid model acts more like a physics-based model, resolving more of the underlying dynamics but in a computationally efficient way. This approach represents an area of research that is largely untapped.

Data assimilation, the use of data to automatically calibrate models, is the impetus for using combined process-based models to make large-scale predictions—it is much easier to incorporate data into process-based models than physics-based models. Many advanced data-assimilation methods exist to extract meaning from noisy, sparse signals of observed shoreline change. However, increased utilization of data assimilation necessarily requires increased data collection: Data assimilation is irrelevant in the absence of data to assimilate. Therefore, increased large-scale and long-term shoreline monitoring efforts are critical to our ability to predict and adapt to long-term shoreline response to climate change.

Thoughtful integration of models and data or the lack thereof permits or prevents believability of the model, respectively. To assess the reliability of model predictions, we must demonstrate the model's ability to reproduce observed behavior.

Illuminating long-term behavior from observed shoreline data is an immensely challenging endeavor. Transient short-term seasonal erosion caused by large waves and storms masks the persistent long-term

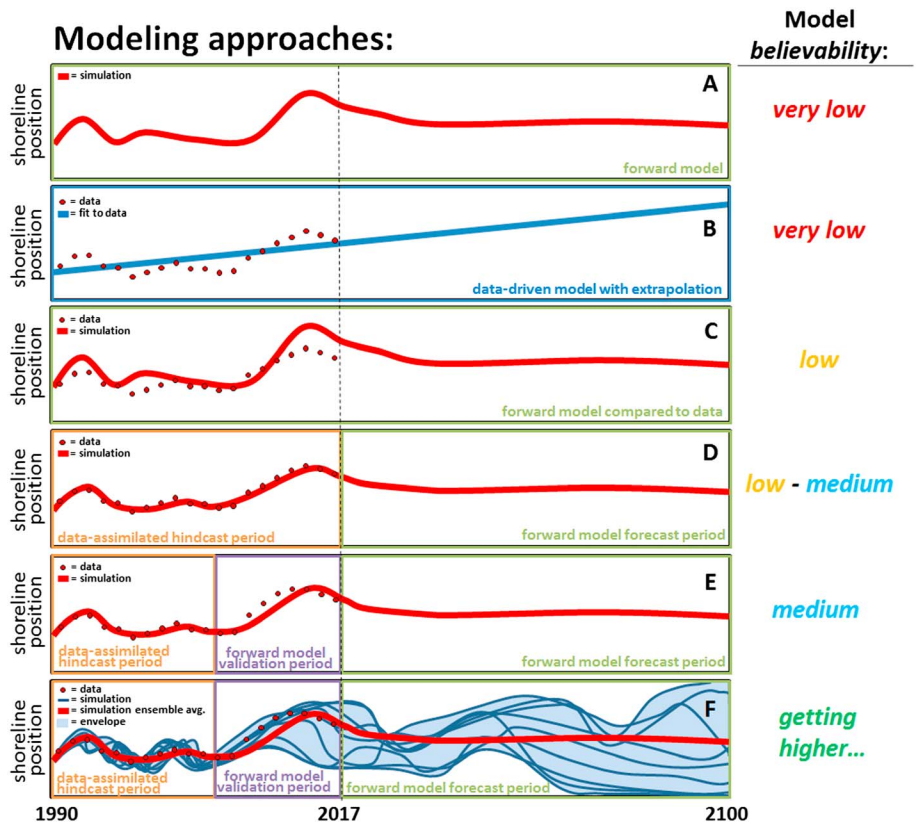

Figure 2. Different modeling approaches: (a) forward model (without calibration/validation data); (b) data-based empirical model with extrapolation; (c) forward model compared to data; (d) data-assimilated forward model and prediction; (e) data-assimilated forward model for calibration, validation period, and prediction; (f) *ensemble* of data-assimilated forward models for calibration, validation, and prediction. The believability of the model prediction generally increases from top to bottom.

signal of shoreline change in the same way that ocean tides mask gradual sea level rise. Predicting long-term response to climate change should be the model's ultimate goal. However, capturing short-term shoreline variability (e.g., erosion and recovery from individual storms) is a worthy goal if only to extract meaningful information about the long-term processes hiding within the noisy shoreline data.

Figure 2 illustrates various approaches to integrate models with data. Applying a forward model without supporting data (Figure 2a) should be met with skepticism about prediction reliability. Likewise, fitting a data-driven model (Figure 2b) and extrapolating should also be met with skepticism, especially when used to make predictions about a changing climate. Applying historical data to validate the model ("hindcasting") (Figure 2c) improves the believability of the forecast. Using data-assimilated models (Figure 2d) also increases forecast believability, as the model is in some sense "trained" with the data. Believability is further increased when data-assimilated models are applied to calibrate model behavior (Figure 2e) and a separate validation period is used to assess performance before the forecast. Finally, the most believable prediction (Figure 2e) will likely come from the combination of a data-assimilated hindcast, validation, and forecast derived from an ensemble of models by using different assumptions about the future wave climate and sea level rise.

Seeking reliable predictions for an inherently nonlinear system, we must use an ensemble of models. Predictions of shoreline change must also consider a range of human intervention (e.g., beach nourishments and seawall or groin construction) [*Ells and Murray*, 2012], which can have a larger impact than climate [*Slott et al.*, 2010]. Using an ensemble of computationally expensive models (e.g., 3-D physics-based models) becomes significantly less practical. Therefore, ensemble model predictions will likely use computationally efficient process-based models and/or statistical downscaling [*Antolínez et al.*, 2015; *Rueda et al.*, 2017] versus dynamical downscaling (i.e., nested models).

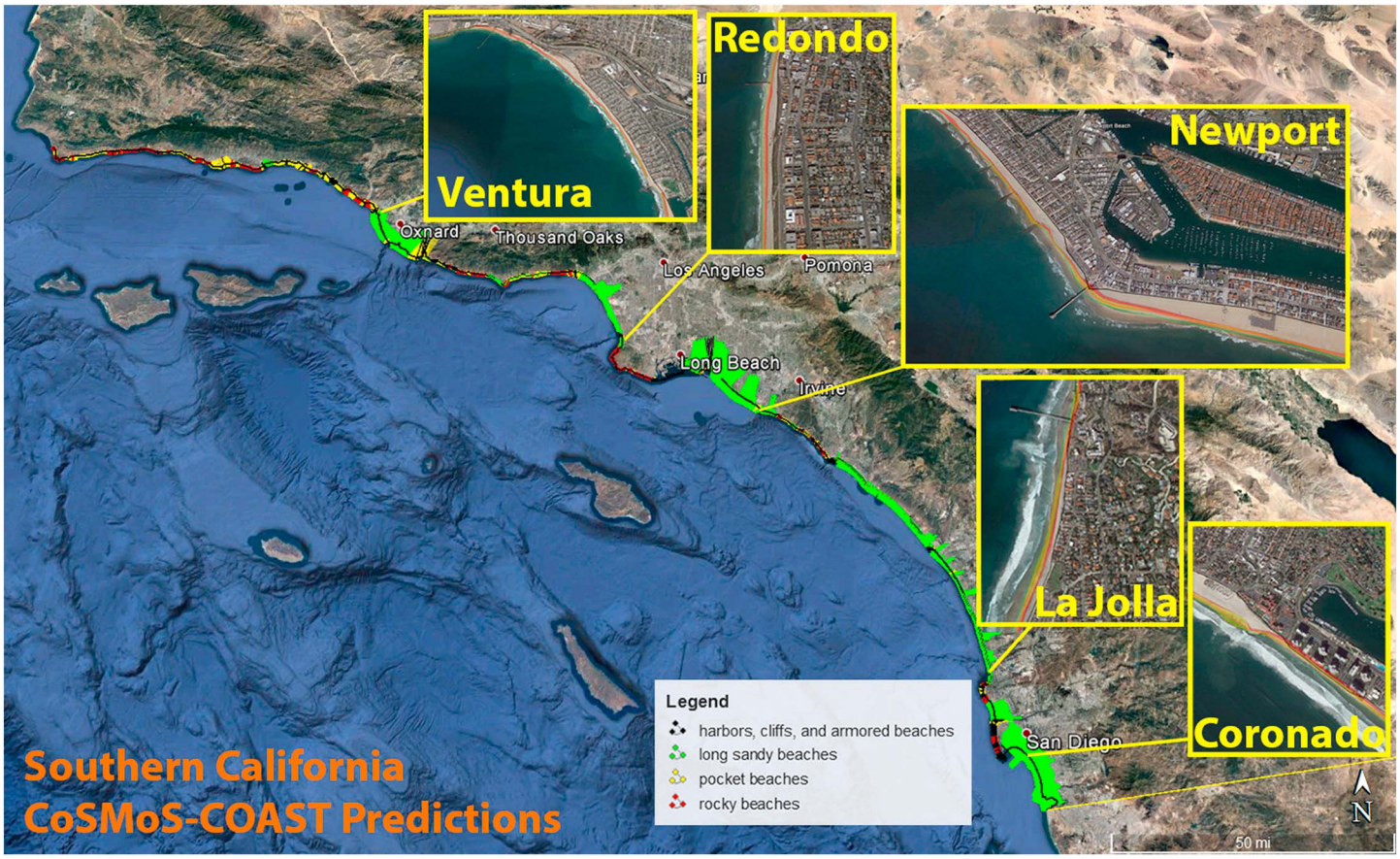

Figure 3. Shoreline modeling predictions for 500 km of coastline in Southern California produced by the CoSMoS-COAST model [*Vitousek et al.*, 2017]. The predictions represent the shoreline position in 2100 with 1.0 m of sea level rise. The yellow bands represent the projected shoreline position and uncertainty. The red bands represent the projected shoreline position and uncertainty during a year with larger than average wave heights.

Large-scale, ongoing coastal hazard assessment projects, e.g., the U.S. Geological Survey's Coastal Storm Modeling System (CoSMoS) [*Barnard et al.*, 2014], have driven numerous advancements in modeling and monitoring [see e.g., *Erikson et al.*, 2015; *Vitousek and Barnard*, 2015; *Limber et al.*, 2015; *Hegermiller et al.*, 2016; *Hoover et al.*, 2016; *Vitousek et al.*, 2017]. Recently, the CoSMoS project completed predictions of long-term coastal flooding, shoreline change, and cliff retreat along 500 km of coastline in Southern California, and the ongoing effort continues northward along the California Coast. Using the newly developed CoSMoS-COAST model (Coastal One-line Assimilated Simulation Tool) [*Vitousek et al.*, 2017], projections of shoreline change in Southern California indicate that 31% to 67% of beaches may completely erode up to existing infrastructure by 2100 without large-scale interventions (Figure 3). These projections pose a dire future for many of California's iconic beaches and the economic, recreational, and protective benefits they provide. Furthermore, these scenarios of beach loss are not unique to California but may become existential issues for coastal communities throughout the world.

3. Future Research and Applications

It is clear that we cannot develop predictions of shoreline dynamics without computer modeling. Yet it is also clear that we cannot develop reliable predictions without extensive shoreline monitoring. Currently, shoreline monitoring plays a paramount role in understanding present-day shoreline variability, trends, and response to physical forcing, and it will become increasingly important for prediction. To this end, we must utilize existing and emerging technology in order to reduce the cost of obtaining accurate shoreline data as the scale of monitoring is expanded to higher resolution in space and time. Aerial LIDAR and ground-based GPS surveys (typically conducted twice a year, at best) represent the current state-of-the-art in mapping

coastal topography and shoreline positions. While these technologies represent worthwhile solutions for developed coastlines, they are often prohibitively expensive for undeveloped nations and coasts. Emerging technologies, such as aerial drones outfitted with high-resolution digital cameras combined with computer vision algorithms (e.g., Structure-from-Motion photogrammetry), can produce digital elevation models with accuracy comparable to lidar for a fraction of the cost [*Warrick et al.*, 2016]. Data and imagery from Earth-observing satellites (e.g., Landsat and Sentinel) remain a largely untapped but emerging source of coastal-change data with high temporal resolution [*García-Rubio et al.*, 2015]. Crowd-sourced data from beach-goers with smart-phones also represent a tremendous potential resource [e.g., *Behrens et al.*, 2009; *Liu et al.*, 2014].

The effects of dunes or coastal cliffs are often neglected when modeling beach dynamics on short time scales. However, predicting long-term coastal response to sea level rise will likely require models that integrate the dynamics of the beach and back-beach systems (e.g., cliffs, dunes, and infrastructure). To this end, data-integrated models of coupled beach and cliff dynamics [e.g., *Limber and Murray*, 2011; *Young et al.*, 2014] will become increasingly important to develop as sea level rise causes chronic erosion, increases wave impacts to cliffs [*Trenhaile*, 2011], and accelerates cliff retreat rates [*Walkden and Dickson*, 2008; *Limber et al.*, 2015]. However, even with these improvements, the ultimate accuracy of projections of coastal change will still be hindered by the uncertainty of the forcing and boundary conditions that drive the model, namely, future sea level rise, storm patterns, wave climate, and sediment supply changes.

4. Conclusions

The science of the coastal zone is bursting at the seams with unanswered questions. But in our opinion—speaking as scientists, surfers, and photographers—the most important question pertaining to the fate of the coastal zone is as follows: how much will sea levels rise in 50–100 years?

The next time you visit the beach at high tide, picture what the beach and surrounding area would look like with an additional meter or two of sea level. We suspect that you may come to the unsettling conclusion that the coastal zone may look very different without large-scale interventions. As another thought experiment: Try to quantify the economic value of 1.0 m of sea level rise. We suspect that you may come to the conclusion that spending money on understanding the science of climate change, adapting to the problem, and reducing long-term impacts will be *cost-effective*. For example, with beaches in California currently generating ~$40 billion for the economy [*Kildow et al.*, 2014], what level of investment is justified to better protect that asset?

The silver lining to the looming cloud of climate change is that sea level rise is a gradual process and, with a motivated effort, we might have a decade or more to understand, plan, and adapt.

How do beaches respond to climate change? The answer to this question hinges on several uncertainties associated with the climate system, sea level rise, and our actions going forward. However, if we were to pose an answer to this question, it would be as follows: the future of the coastline *will be what we engineer it to be*. Sea level rise may leave us with few other options.

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