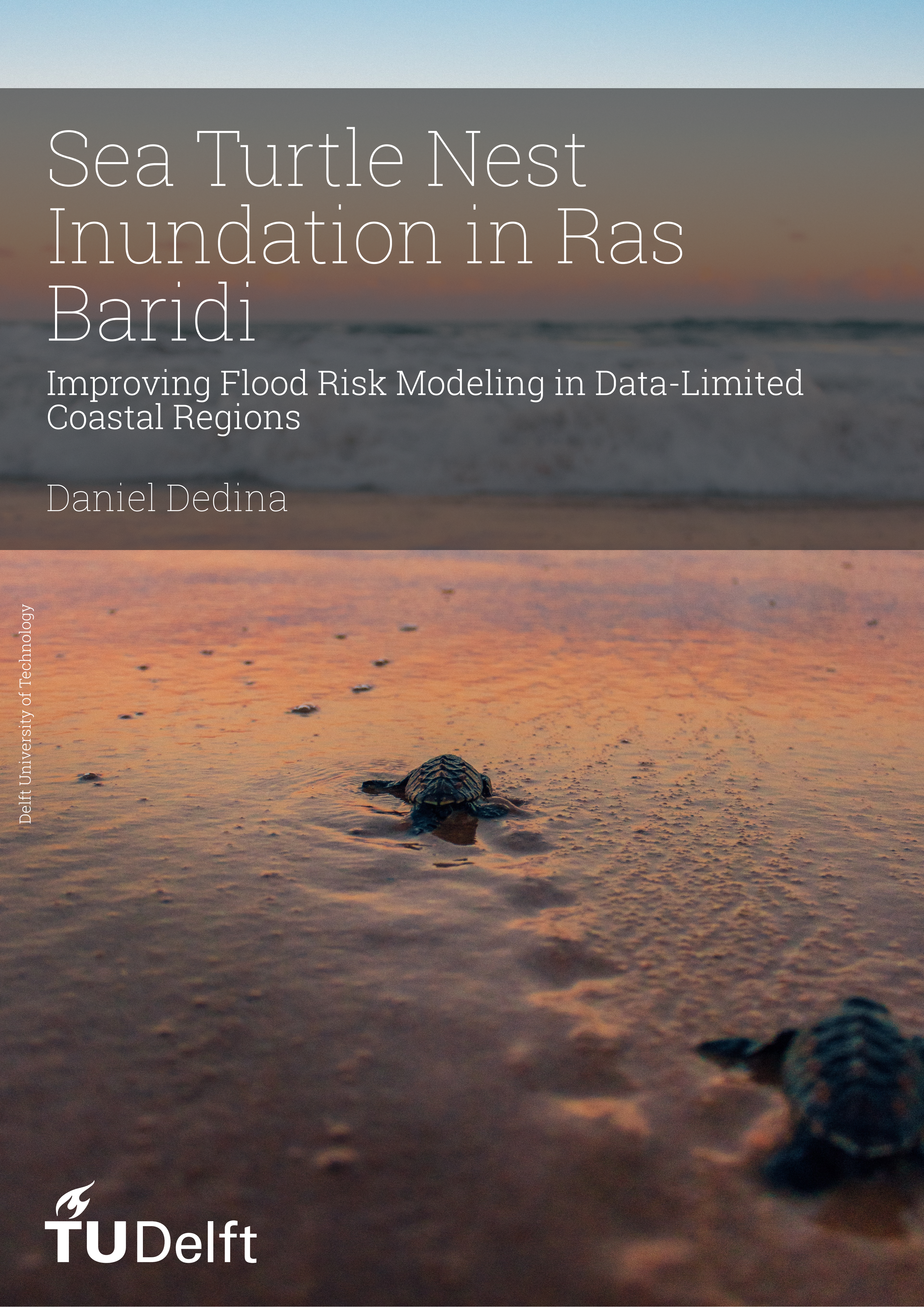

Sea Turtle Nest Inundation in Ras Baridi

Improving Flood Risk Modeling in Data-Limited Coastal Regions

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Improving Flood Risk Modeling in Data-Limited Coastal Regions

by

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Cover: Marine turtle hatchlings making their way to the sea, courtesy of Lucas Meneses

TU Delft

Executive Summary

Six out of the seven sea turtle species are listed as endangered by the IUCN. Sea turtle eggs exhibit remarkable sensitivity to fluctuations in temperature, salinity, and moisture during their 6-8-week incubation period. Inundation of these eggs can substantially decrease their viability and influence sex ratios. This thesis centers on mitigating the wave runup-driven flooding of sea turtle nesting beaches.

In practice, mitigating nest flooding can involve either reducing incoming waves and water levels or relocating at-risk nests to higher elevations. The optimal height for nest relocation is dependent on local hydrodynamics and bathymetry, and is vital information to ensure the successful safe relocation of a nest. This thesis aims to assist in responsible nesting relocation by providing flood risk information as a function of beach elevation.

The study site, Ras Baridi, is a significant nesting site for green turtles (*Chelonia mydas*) in the Red Sea. The site features a beach fronted by a coral reef of varying width (80-170 m). There is very little environmental data measured locally that was available for use in this study. For this reason, the research questions encompass the development of a methodology for assessing flood risk in environments with limited data, the resolution of uncertainties in wave runup modeling, and the evaluation of existing metamodels' performance in these conditions.

The risk of sea turtle nests to flooding at Ras Baridi was assessed by employing two different metamodels, BEWARE 2.0 and HyCReWW, that were recently developed to assess wave runup in coral reef environments at low computational costs. These models employ different strategies to model wave runup. BEWARE 2.0 uses a database of real bathymetry profiles and a database of XBeach 1D Non-hydrostatic model runup results. HyCReWW schematizes the reef using 4 parameters, and interpolates to a database of XBeach 1D Non-hydrostatic results based on the input hydrodynamics.

40-year hindcast datasets of waves and water levels from 1978-2018 were used in combination with 10 m horizontal resolution bathymetry data from the Allen Coral Atlas as model inputs. The metamodel results in Ras Baridi were presented for 4 different profiles across the beach, representing the varying reef widths from 80-170 m. To analyse inundation risks, wave runup was computed for return periods (RP) of 1 to 40 years. HyCReWW exhibited maximum runup at an 80 m reef width (0.95 m for 1 year RP, 1.95 m for 40 year RP) and minimum runup at a 170 m reef width (0.9 m for 1 year, 1.9 m for 40 years). BEWARE 2.0 showed its lowest runup at an 80 m reef width (1.35 m for 1 year, 2.7 m for 40 years) and maximum runup at 170 m reef width (0.85 for 1 year RP and 1.8 for 40 year RP).

The duration of modeled runup events is crucial in understanding flood risk to sea turtles, with a 6-hour inundation reducing egg viability by as much as 30%. Median inundation durations from BEWARE 2.0 and HyCReWW were 4 and 7 hours, respectively. To ensure nest safety during the 50-70 day incubation period, elevations associated with 5-year return periods were identified as suitable minimum nesting elevations to mitigate inundation risk.

BEWARE 2.0 and HyCReWW results for Ras Baridi lacked direct real-world validation, prompting a methodological validation approach. Six validated XBeach 1D NH models in fringing reef environments globally were utilized for comparison against BEWARE 2.0 and HyCReWW. The comparison revealed increased median scatter indices and root-mean-square (RMS) errors for both BEWARE 2.0 (0.07 and 0.1 m increases) and HyCReWW (0.1 and 0.15 m increases) with low-resolution bathymetry (10 m horizontal). BEWARE 2.0 had lower median RMS errors and scatter indices for high-resolution (2 m horizontal) and low-resolution bathymetry than HyCReWW, as well as smaller spreads. Consequently, utilizing BEWARE 2.0 results is recommended for Ras Baridi and similar data-scarce coastal environments over HyCReWW.

In summary, this thesis addresses the pressing issue of sea turtle nest flooding, providing a methodology to assist in responsible nest relocation in low data environments. The 5-year return period runup elevation of the BEWARE 2.0 results (1.25-1.75 m along the beach) has been identified as a suitable minimum nesting elevation in Ras Baridi, and the likelihood of flooding as a function of beach elevation has been provided. These results can aid coastal managers in making informed decisions for the protection of these endangered species.

Preface

This thesis completes the Master of Science in Coastal Engineering and marks the end of my time at Delft University of Technology. The past nine months of thesis work and two and a half years of study in the Netherlands has been difficult, rewarding and enriching to the utmost degree. I feel so grateful to have been able to study a subject I find deeply interesting, surrounded by fellow students and professors who feel the same. However, without the help and guidance of others, I probably would not have made it out of my first quarter, let alone hand in my thesis.

I would like to thank my supervisor, Ir. Jakob Christiaanse, for his constant, even-keeled support. His guidance during our weekly meetings proved essential to the completion of this thesis. His advice, even if I didn't always immediately take it, usually turned out to be spot on. Next, I would like to thank my Committee Chair, Dr. Ir. José Antonio Álvarez Antolínez, for his ideas and unwavering optimism. His ability to find solutions when I could only see problems was inspiring. His recommendations seemed to come precisely when I needed them most, and often led the work in the right direction. I would also like to thank Ir. Floortje Roelvink, whose contributions and expertise with BEWARE 2.0 were critical to helping complete the project. Her willingness to run many simulations on her own time was greatly appreciated, as was her feedback during meetings and on the drafts. Many thanks go to Dr. Ahmed Elshinnawy for the use and guidance in the use of his Red Sea wave model. Furthermore, I would like to thank Prof. Ir. Ad Reniers for his modeling expertise and critical feedback of my drafts, which reminded me of the importance of questioning my own assumptions.

Finally, I would like to thank my friends, Alkis, Akis, Emmy, Kirykos, Meye, and the many others at TU Delft who have provided support and levity when I was feeling stressed. I have endless gratitude for my gracious and patient girlfriend Madeline, who supported and encouraged me even though it required me to be half a world away from her. I would like to thank my friends and family in the US for always lending an ear for me vent to, and letting me know that they were rooting for me. I would like to especially thank my parents, whose support and guidance has allowed me to achieve my goals.

Daniel Dedina
Scheveningen, October 2023

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Nomenclature

Abbreviations

Abbreviation	Definition
ACA	Allen Coral Atlas
BEWARE 2.0	Bayesian Estimator for Wave Attack in Reef Environments 2.0
GEE	Google earth engine
GEBCO	General bathymetric chart of the oceans
GTSM	Global tide and surge model
HyCReWW	Hybrid Coral Reef Wave and Water level
IPCC	International Panel on Climate Change
IUCN	International Union for Conservation of Nature
LHS	Latin hypercube sampling
MHW	mean high water
MSL	mean sea level
NCEI	National Centers for Environmental Information
NH	non-hydrostatic
NOAA	National Center for Oceanic and Atmospheric Sciences
OAT	one at a time
POT	Peak-over-threshold
RB	Relative bias
RP	Return period
RMSE	Root-mean-square error
RSLR	Relative sea level rise
SA	Sensitivity analysis
SI	Scatter index
SLR	Sea level rise

Symbols

Symbol	Definition	Unit
c_f	Coefficient of friction	
D_{50}	Median grain size diameter	[m]
H_s	Significant wave height	[m]
H_s/L_0	Wave steepness	
Q	Exceedance probability	
S_1	First order sensitivity index	
T_p	Peak period	[s]
N_s	Number of storms per year	
WL	Water level	[m]
W_r	Water level	[m]
δ	Borgonovo's delta	
β_b	Beach slope	
β_r	Fore-reef slope	
η_0	MSL proxy	[m]

1
Introduction

This chapter sets the stage for the research by highlighting the significance of sea turtle conservation and the specific challenges faced in the study area, Ras Baridi. It outlines the research objectives and questions that will be addressed in the study.

1.1. Motivation

Sea turtles are facing a variety of threats from anthropogenic climate change (Ware et al., 2021), destruction of habitats and fishing activities (Mancini et al., 2015). Because of these threats, six of the seven species of sea turtles worldwide are designated as endangered or vulnerable by the International Union for Conservation of Nature (IUCN) (Abreu-Grobois and Plotkin, 2008). The fate of sea turtles is tied strongly to temperature and storm events, making them a bellwether species for climate change impacts on coastal species (Hawkes et al., 2009). Sea turtles are also important in maintaining ecosystem health, through their feeding and nesting habits and position within different marine food webs (Mancini et al., 2015), so they are an important species to study. Rapid changes in nesting area (erosion, land development, pollution) and climatic conditions (atmospheric temperature, sea surface temperature, hydrodynamics) highlight the vulnerable positions of sea turtle populations. Coastal flooding and coastal development endangers nesting space (Pike et al., 2015) and temperature changes reduce hatching success rates and affect population sex ratios (Hawkes et al., 2009). Increased ocean temperatures affect the spatial distribution of feeding areas for adults (Hawkes et al., 2009).

While sea turtles have existed for over 100 million years and have survived past changes to global temperatures, the current rate of change is more rapid than previous events and it is unclear whether sea turtles can adapt quickly enough to the rapid environmental changes they face (Mancini et al., 2015). Sea turtle populations are globally distributed and require site-specific action due to the wide variety of environmental conditions of their habitats (Mancini et al., 2015). Regionally quantifying the impacts to species is the first step to responding to and mitigating the risks that sea turtles face (Pike et al., 2015).

A major threat that sea turtles face is the degradation of their nesting beaches. The long-term disappearance of nesting beaches due to increased erosion rates, future projections of hydrodynamics under SLR scenarios (Luijendijk et al., 2022), and intense flood events during the nesting season are adversely affecting sea turtle populations (Ware et al., 2021). Sea level rise, combined with new developments along the shoreline causes narrowing of beaches, or 'coastal squeeze.' This leaves less space for turtles to nest at higher elevations and leaves their nests exposed to a wider range of storm events. As sea levels rise, natural wave barriers such as fringing coral reefs will lose their ability to dissipate wave energy, and beaches will erode at increasing rates (Luijendijk et al., 2022), which will further increase the risk of flooding. Coastal flooding attributed to wave motion at the shoreline, or wave runup, has the potential to wash away nests under extreme conditions.

Nests are extremely vulnerable to flood events. sea turtles do not receive post-natal care, so the survival of sea turtles depends on the female laying a large number of eggs, as each egg individually has a small chance of survival until adulthood. Nesting sites are characterized by specific climatic conditions that are necessary for egg viability (Pike, 2013). The salinity, moisture, and temperature of nests play a pivotal role in the development of hatchlings (Ware et al., 2021; Mancini et al., 2015; Pike et al., 2015). For more details on sea turtles' nesting habits in the Red Sea, see appendix B.

Inundation of sea turtle eggs reduces their viability. Because of the six- to eight-week incubation period, rising seas and more frequent flood events leaves nests very exposed to inundation. A case study of green turtle egg inundation on Raine Island, Australia, the largest rookery of green turtles (*Chelonia mydas*) in the world, showed the temporal dependence of egg inundation. Eggs that were submersed for 1-3 hours reduced viability by 10% and inundation for 6 hours reduced viability for approximately 30% (Pike et al., 2015).

To protect nests from inundation, it is common practice for coastal managers to relocate nests to higher elevations when they are below or near the high tide line (US Fish and Wildlife Service, 2008). There is no standard criteria for moving nests to higher locations. While this practice can be effective for protecting against inundation, moving a nest also poses risks for the eggs and could change incubation conditions, effecting mortality rates and sex ratios (Ware et al., 2019; Tuttle and Rostal, 2010; Ahles and Milton, 2016). A well-defined risk level for moving a nest will diminish the risk of unnecessary nest movement.

Relocation of turtle eggs is time sensitive as well. As a general rule, nests should be relocated within 12 hours of being deposited by a female, because eggs have very sensitive gas-exchange membranes that develop rapidly after the eggs have been deposited (Ahles and Milton, 2016). There is correlation between relocation times later in the incubation period and increasing mortality rates of eggs (Ahles and Milton, 2016). This suggests that, from a management perspective, efficient and effective mitigation measures would be preventative and not in response to forecasted high water levels.

Preventative measures would include designating a safe flood level to relocate nests, and carrying out periodic monitoring campaigns during the nesting season to designate which nests are below the safe elevation. For that to happen, coastal managers need a quantitative assessment of the flooding likelihood along the beach elevation so that they may reduce the flood risk. The benefits are twofold: quantifying flood levels is important to know for flooding of nearby coastal areas, and it aids the management of nest flooding.

An ideal location for the study of flood risk to nests is in the Red Sea, where five of the seven sea turtle species can be found (Mancini et al., 2015; Shimada et al., 2021a,b). Two of those five species, green and Hawksbill turtles (*Eretmochelys imbricata*), nest annually on islands and coastlines throughout the sea (Mancini et al., 2015). The longest studied and most popular nesting beach for green turtles within the Red Sea is the six kilometer beach of Ras Baridi (Shimada et al., 2021a). Many sea turtle nesting beaches are located in remote subtropical and tropical areas of the world (Wyneken et al., 2013; Pike, 2013), which feature coral reefs offshore of the beach, or fringing reefs. Ras Baridi features a fringing reef, making it representative of other nesting beaches. It is also a location that will desperately need to mitigate the risks of coming sea level rise (SLR), as the rates of sea level rise in the Red Sea exceed the global mean by 3-4 times (Becker et al., 2012).

This study aims to quantify the risk of green turtle nest inundation by wave runup at Ras Baridi. Quantifying flood levels typically requires highly accurate, site specific environmental data that is not readily available for use in Ras Baridi. Such low data environments in the context of numerical modeling are characterized by a limited availability of high-quality and comprehensive data necessary for accurate and reliable modeling. Several factors can contribute to this scarcity. In Saudi Arabia, sparse monitoring stations that record wave and water level data leave spatial gaps in data. There is also a lack of historical data of water levels and waves, making it difficult to establish long-term trends. While there may be privately-held data sets that could be useful for researchers, they are not publicly available. These issues are not not unique to Ras Baridi, but exist in many sea turtle nesting regions. Despite the lack of data, quantifying and mitigating flood risk in these areas is essential for sea turtle conservation efforts.

1.2. Research objective

1.2.1. General approach and scope

There are three main mitigation pathways to nest inundation: moving at-risk sea turtle nests to higher elevations, reducing the runup capability of waves or a combination of both by decreasing the incident wave heights, the total water level, or both (Ware et al., 2021). This report focuses on moving at-risk sea turtle nests to safe elevations, defined by a low risk of flooding.

The beaches of Ras Baridi are major nesting sites for the endangered green turtle. From 2018-2019, 254 individuals were reported to have nested annually (Shimada et al., 2021b). Reports of consistent overwashing of nests during nesting season from local researchers has provided impetus for a flood assessment. The objective of this research is to provide coastal managers with tools to assess and mitigate flood risks to sea turtle nests. Coastal managers need effective measures that are based on accurate assumptions to properly respond to the issues at hand. Ras Baridi is a low data environment, providing distinct challenges to accurately addressing the problems that sea turtles face.

To that end, the processes causing flooding have been identified and are simulated with two meta-models. Typically, coastal managers will relocate at-risk nests to higher elevations, but moving nests too high poses risks for hatchlings' ability to reach the water. Due to the delicate nature of incubation, it is also important that sea turtle nests are moved as early in the incubation period as possible (Ahles and Milton, 2016). Due to restricted beach widths from landward construction, there is limited space to move nesting sites. Defining a safe nesting elevation ensures that nests are moved out of the range of high frequency flood events, can be moved early in the incubation period, and that hatchlings are not positioned so high that they cannot reach the water. Safe nesting elevations can also provide clear limitations for any future construction plans on the coastline. The acceptable risk of flooding can then be left to the actual managers. Thus, the primary goal is to define for Ras Baridi an estimate of flooding likelihood as a function of beach elevation that coastal managers can reference when nesting relocation is necessary.

1.2.2. Research questions

The primary research question that this thesis aims to answer is: What is the likelihood of sea turtle nest inundation as a function of beach elevation at Ras Baridi? These sub-questions can be pursued to answer the primary research question:

- What is a user-friendly and globally applicable methodology for assessing the flood risk of a fringing reef coastline in a low data environment?
- How do BEWARE 2.0 and HyCReWW perform in low data environments?

1.3. Site Description: Ras Baridi

Located on SA's northwestern coast, Ras Baridi is fronted by fringing coral reefs about 50-100 meters offshore that are inhabited by a myriad of species of fish. The reefs range in width from 50-200 meters wide and drop steeply on the seaward side into deeper water, and function as protective barriers against wave action. Extensive seagrass beds are also present, making this area an important feeding ground for sea turtles.

The waves in the northern Red Sea are generally wind-generated and are predominately from the north and northwest, with significant waves heights of approximately 1 meter year-round. Longer period waves (>6 s) come from the south and do reach the northern coasts, usually from the months of October to April. The largest waves are generated in the central Red Sea from strong seasonal winds from the east out of the Tokar gap (Langodan et al., 2017).

The tidal regime is semi-diurnal and the tidal range in the Red Sea ranges from 1 meter in the north to 0.2-0.3 meters along the central coast where Ras Baridi is located (Luijendijk et al., 2022; Mancini et al., 2015). Complex air-sea dynamics with strong spatial variability across the Red Sea control short-term (days to weeks) sea level changes (**?**). A year-long measurement of offshore wind stresses and nearshore pressure/salinity/temperature measurements in the central Red Sea provided insight into weather driven sea level changes. It was found that local wind-driven Ekman transport accounted for short-term set up and set down of up to 30 cm (**?**). Annual sea level variability in the central Red Sea on the order of the tidal range (30 cm) has been attributed to the seasonal changes in wind direction, with higher sea average sea levels measured in the winter, and lower sea levels in the summer (**?**). Evaporation in the summer also effects sea level changes, albeit less than the wind stresses (**?**). For more details on the physical description of the Red Sea, see appendix A.

The high density of sea turtle nests and ecological value of Ras Baridi make it an important area to study and its physical characteristics also make it an suitable case study for flood risk. Ras Baridi is located along the mainland where the hydro- and morphodynamics are simpler than the complex island systems of the Al Wajh Bank where there are also a large quantity of nesting beaches.

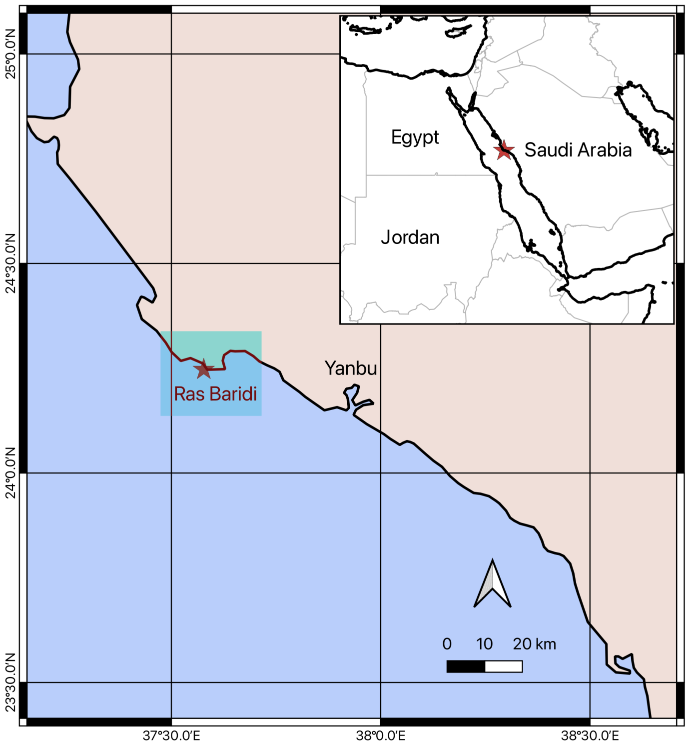


Figure 1.1: Map of Ras Baridi and surrounding area

1.3.1. Coral reef hydrodynamics

Coral reefs serve as a natural flood protection device. Fringing corals reefs are situated offshore, jutting up from deeper water. As waves approach the reef from offshore, they are forced to shoal and break, which can dissipate as much as 97% much of their energy before they reach the shore (Ferrario et al., 2014). Most of this energy is dissipated by reef crest, through wave breaking and the large roughness values of the reef geometry. The energy loss associated with breaking on the reef is then excluded from the potential for waves to break and run up on the shore, or entrain sediment in the water column. The erosive capability and the flooding capability of the waves are diminished in a similar manner to a submerged breakwater.

The hydrodynamics of the coastline of Ras Baridi can be characterized by the reef present, as they dictate the processes that occur. The reefs can be described by three primary features: the fore-reef, the reef crest and the reef flat or back reef. The fore-reef of Ras Baridi is steep and drops off into deeper waters and contains the highest diversity of corals due to the circulation patterns and nutrient distribution. The reef crest is shallow and ranges in width (50-200 m) and depth (0-2 m). The reef flat is located between the crest and the shore and is typically an area with calm hydrodynamics featuring small reef and seagrass patches.

Fringing reefs' effect on long waves is less pronounced. Long waves or infragravity waves with period of 25 s to 250 s are primarily responsible for wave runup. Recent studies have shown that they are present after sea or swell waves dissipate across a reef and continue towards the shoreline (Franklin and Torres-Freyermuth, 2022). Reef induced wave breaking also increases wave set up, increasing the total water level at the shoreline and enhancing the runup capability of long waves (Buckley et al., 2022). Reef geometries can also trap certain long wave frequencies at the shoreline and resonantly amplify long waves (Buckley et al., 2022), further increasing runup.

Most empirical wave runup models were developed for simple sandy beach profiles with little variation in slope (Stockdon et al., 2006; Franklin and Torres-Freyermuth, 2022), and are not valid for reef environments. However, attempts at understanding the most important parameters for modeling of hydrodynamics on reefs have been made (Rueda et al., 2019; Cheriton et al., 2016; Buckley et al., 2022; Pearson et al., 2017; Franklin and Torres-Freyermuth, 2022; Scott et al., 2020). Most important are the hydrodynamic forcing and the reef geometry (reef width and fore-reef slope) (Franklin and Torres-Freyermuth, 2022). Roughness of the reef flat plays a role in wave dissipation, but whether or not the influence is as important as the aforementioned parameters varies by study (Pearson et al., 2017; Buckley et al., 2022; Cheriton et al., 2016). Bottom roughness may also be degrading due to a climate change-induced increased wave energy which prevents the vertical growth of coral structures (Baldock et al., 2014), although this is not known for Ras Baridi. Thus when modeling wave transformation over reefs, all of these factors are important to take into account.

2
Methods

This section describes the methodology used for the modeling of runup in Ras Baridi. Specifically, the model input data is described, the metamodels are described, handling of the different uncertainties is discussed, and the methods of analyzing the data are presented.

2.1. General approach

The project area is a low data environment, where very little in situ data was available. The approach to achieving the study goal of finding the likelihood of sea turtle nest inundation as a function of beach elevation at Ras Baridi will be based on handling the uncertainties of numerical modeling using low resolution remote sensing data and global model data.

The first stage of the approach includes using two recently developed 1-D wave runup metamodels, HyCReWW and BEWARE 2.0, to create time series of wave runup (figure 2.1. A 1-D model resolves waves and water levels in the cross shore direction. This is useful for simple topobathy data, where the profile is relatively similar in the long shore direction. It is also useful for runup, where the desired result is the water surface elevation at the shoreline. However, moving from 2D to 1D simplifies the hydrodynamics, and can leave out processes that play a role in runup, like refraction, short wave directional and frequency spreading (Reniers et al., 2002; Guza and Feddersen, 2012), and longshore currents. The models employ two different strategies: HyCReWW parameterizes the input bathymetry profile, while BEWARE 2.0 uses real bathymetry profile. Because these two approaches differ significantly, their results are important to compare.

The results cannot be validated with measured in-situ runup data, so the performance of the two metamodels will be compared to each other using validated XBeach model results as a benchmark shown in 2.1. This provides a methodological validation of which metamodel is more suitable to model runup in this environment, and provides insight into the appropriateness of the modeling techniques used.

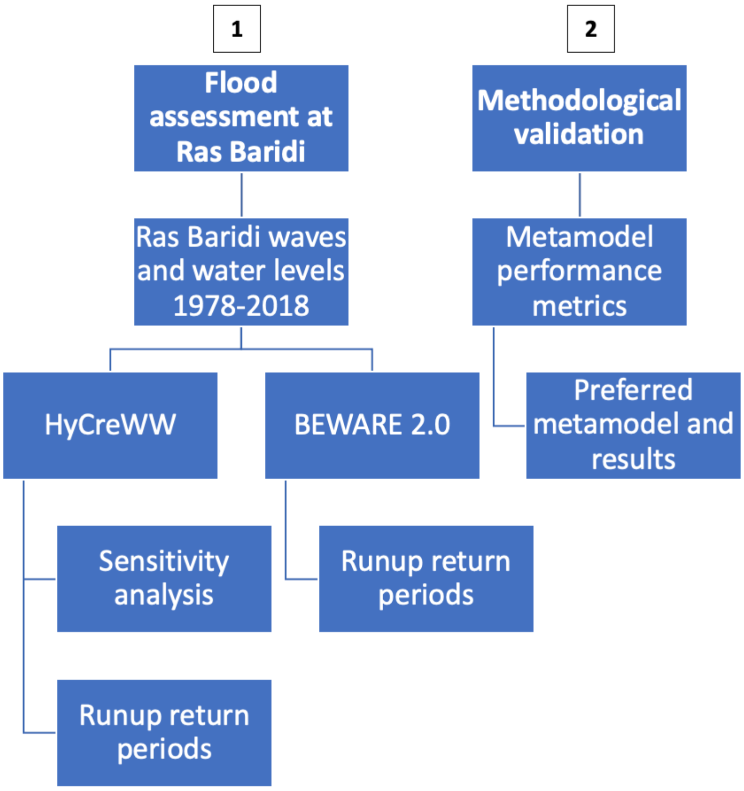


Figure 2.1: The 2 stages of the methods are schematized in a flow chart.

2.2. Available data

The data available for use in the modeling of wave runup at Ras Baridi is described in this section.

2.2.1. Waves

The wave data used in this project was generated from a wave model of the Red Sea. Wind fields from ERA5 atmospheric re-analysis with a spatial resolution of 0.25 degrees and a temporal resolution of 1 hour (Muñoz Sabater et al., 2021) forced the wave model and the General Bathymetric Chart of the Oceans (GEBCO) gridded bathymetry dataset was used for bathymetry. GEBCO is a global terrain model for ocean and land, providing elevation data, in meters, on a 15 arc-second interval grid (Mayer et al., 2018). GEBCO uses data derived from both single-beam and high-resolution multibeam echo sounders, which are superimposed on a base derived from satellite altimetry data (Mayer et al., 2018). The hourly hindcast dataset contains sea state parameters for each grid point, including the H_s, mean wave periods (T_{m01} and T_{m02}), wave direction ($_m$), directional spreading (σ_θ), spectral peak frequency (f_p), and wave energy flux (EC_g). The parameters of the 2D wave spectrum partitioned for one sea and five swell partitions including H_s, f_p, $_m$ and were also stored at each grid point hourly. The spatial and temporal resolutions are 0.05 degrees and 1 hour, respectively. The Red Sea hindcast dataset was validated against in situ buoy records and altimeter observations. The wave rose and period rose shown in figure 2.3 show that the majority of waves come from the northwest and are below 1.5 meters and 4 seconds. Waves of periods 6<T_p<7 seconds very occasionally come from the southeast. The data was extracted in the same bay that the nesting beach is on, as shown in figure 2.2. The proximity of the extraction point to the nesting beach is important, so that the effects of shadowing and refraction could be accounted for as much as possible. In the models used in this report, all waves are treated as shore-normal and in deep water. The depth at the extraction point in the GEBCO bathymetry dataset is 50 meters, which classifies the modeled incoming waves as deep water waves. In figure 2.2, the primary wave direction is nearly 45 degrees to the nesting beach of interest. The small number of waves coming from the south must refract more than 90 degrees to reach the shoreline of the nesting beach. Refraction reduces the incoming wave energy by spreading it, and can lead to a reduction in wave heights. Refraction is not a process modeled in the 1D metamodels used in this report, which means that the incident waves will be overestimated in the models.

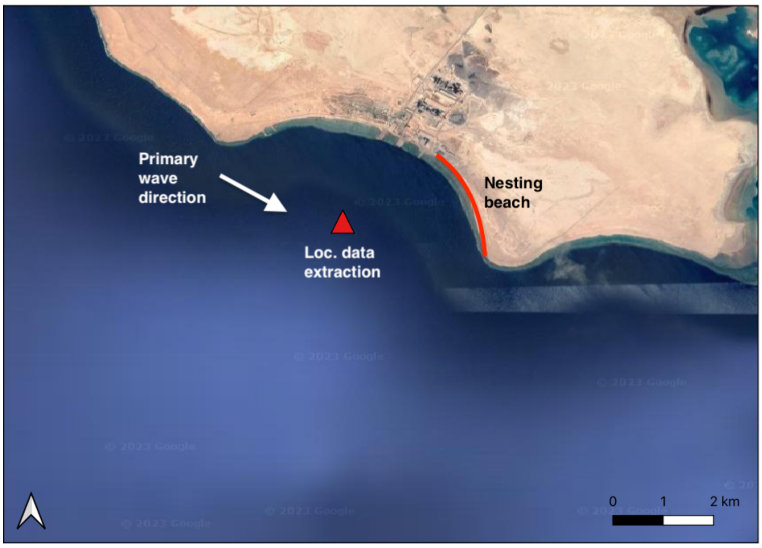
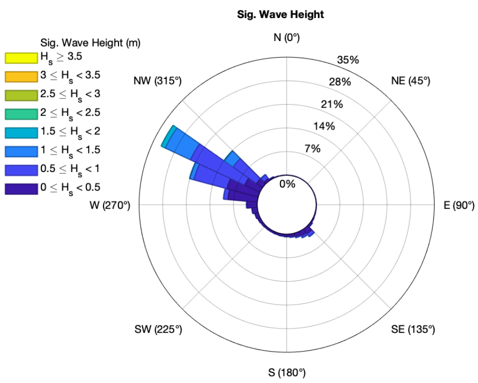
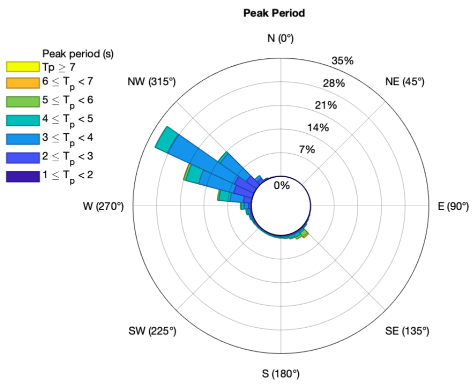


Figure 2.2: Map showing the location where the wave data was extracted from, along with the dominant wave direction.



(a) Direction-intensity graph with significant wave height of the 40 years of wave data from the Red Sea Wave model.



(b) Direction-intensity graph with peak period of the 40 years of wave data from the Red Sea Wave model.

Figure 2.3: Direction-intensity graphs for both significant wave height (left) and peak period (right)

2.2.2. Water levels

Water levels at Ras Baridi were extracted from the Global Tide and Surge model (GTSM) developed by Deltares (Muis et al., 2020). GTSM is a global depth-averaged hydrodynamic model based on the Delft-3D flexible mesh software with spatially varying resolution that increases from a maximum of 25 km offshore to 2.5 km near the coast (Veenstra et al., 2022).

Figure 2.4: Location of the GTSM data extraction point, shown as the white star.

GTSM is forced by the ERA-5 reanalysis of wind and surface pressure. The relative sea level rise (RSLR) is modeled via the EC-EARTH global climate model from the Danish Meteorological Institute (DMI) which imposes the climate forcing (ECWMF, 2023). GEBCO bathymetry data was used in the GTSM model for the Red Sea. The GTSM data was extracted from a grid point at Ras Baridi shown in figure 2.4 and covers 40 years from 1978-2021. In order to reduce computational time, the coastline in the model was smoothed, removing features like bays and estuaries. This reduces the spatial variability that might have been observed in the surrounding inlets and bays of Ras Baridi. The tidal range in the GTSM data is about 0.3 m. The modeled surge ranges from about +0.3 m to -0.3 m shown in figure 2.5. This matches with the literature described in section 1.3. The GTSM model is vertically referenced to mean sea level (MSL) (Muis et al., 2020), but is not locally referenced to a tidal datum.

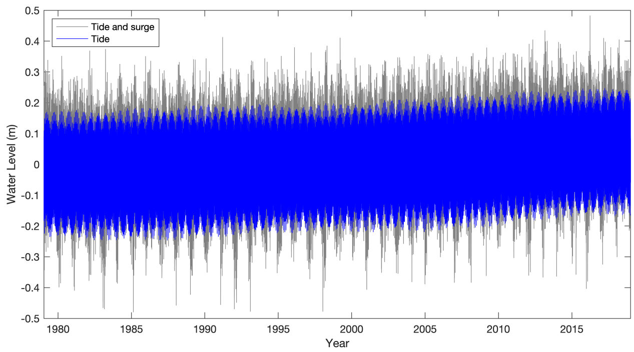


Figure 2.5: GTSM modeled tide (blue) and tide + surge (grey) from 1978-2018.

Due to the climate forcing used in the GTSM model, sea level rise trends over the past 40 years are apparent in the waterlevel data in figure 2.5. In figure 2.5, MSL in 1978 is around -0.05 m, and raises to around 0.03 m by 2018. Tide gauge measurements in the Red Sea from the beginning of the 20th century measured SLR to be 1.7 mm/year (Abdulla and Al-Subhi, 2021), although more recent satellite altimetry data sets from 1993 to 2017 showed and increase of SLR rates to 3.3 $\pm$ 0.5 mm (Abdulla and Al-Subhi, 2021). The total SLR in the data matches with the GTSM value of about 0.08 m. However, using the water level data that contains a SLR trend would cause the SLR to propagate through to the runup results, creating a bias in the analysis of the results. Therefore, the water level data is de-trended using MATLAB's curve-fitting toolbox and a 2nd-order polynomial fit shown in figure 2.6.

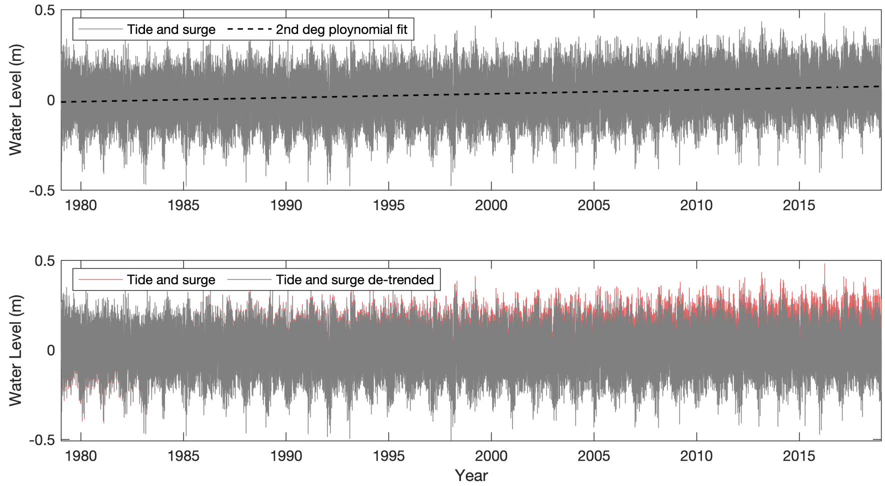


Figure 2.6: The top panel shows the GTSM tide and surge from 1978-2018 along with the 2nd degree polynomial fit from MATLAB's curve-fitting toolbox. The bottom panel shows the de-trended data in red plotted against the original data in grey.

2.2.3. Bathymetry

10-m resolution bathymetry from the Allen Coral Atlas was used, as locally measured bathymetry was not available. The Allen Coral Atlas (ACA) is a publicly available global map of coral reefs generated from satellite imagery and provides 10 m horizontal resolution bathymetry data and can be seen in figure 2.7. The vertical accuracy is unknown. ACA depth data is generated by using the median value of Google Earth Engine (GEE) Sentinel-2 surface reflectance dataset over 12 months (Li et al., 2019, 2021). Detailed methods of how the depths were generated can be found in (Li et al., 2019, 2021). The accuracy of the data sharply declines in deep water. The method of depth calculation used to create the ACA bathymetry is much less reliable deeper than 10 meters (Li et al., 2021). The bathymetry past 10 m depth is provided by ETOPO 2022 Global Relief Model that the United States' National Center for Environmental Information (NCEI) developed. The model has 15 arc-second resolution (about 0.5 km) (NOAA National Centers for Environmental Information, 2022).

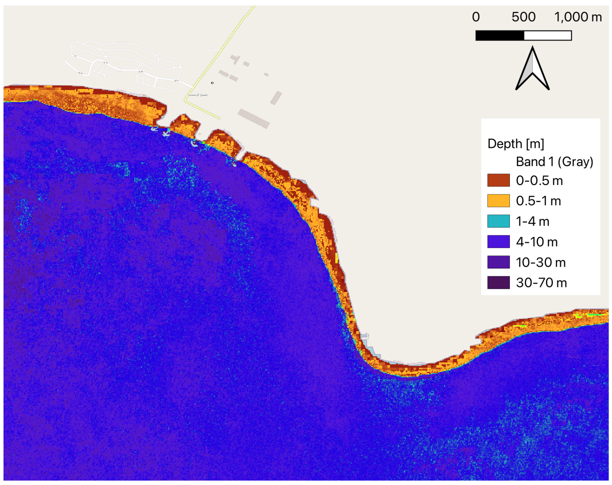


Figure 2.7: Bathymetry heat map of Ras Baridi. The reef flat extent is clearly visible in orange and red.

2.2.4. Sediment data

Sediment data from the beach at Ras Baridi was collected in the spring of 2022. Samples from the waterline, high tide line, and the nesting area were taken along a transect of the beach. The beach sediment on the upper shore-face was poorly-graded medium sand (D_{50} = 0.25-0.30 mm , while the sediment around the water line was well-graded very coarse sand (D_{50} = 2 mm).

2.3. HyCReWW metamodel

The metamodel "Hybrid Coral Reef Wave and Water level" (HyCReWW) is used in this study to generate runup predictions for different reef geometries and wave conditions. HyCReWW relies on a large, synthetic dataset of runup for different reef geometries and hydrodynamics that were generated using 1-D XBeach non-hydrostatic. The model does not include directional spreading and thus all waves are considered to approach perpendicular to the shore. The metamodel is run using a MATLAB script and an input file containing 7 different parameters: the water level, η_0; the offshore wave height, H_0;the offshore wave steepness, H_0/L_0; the fore reef slope, β_f; the reef width, $W_(reef)$; the beach slope β_b; the reef friction factor and c_f. The metamodel then uses Radial Basis Functions to interpolate the user inputs to a run up value. HyCReWW has been validated with field and laboratory studies and is vertically accurate up to less than 30 cm (Rueda et al., 2019). For detailed information on the HyCReWW metamodel, see Rueda et al. (2019).

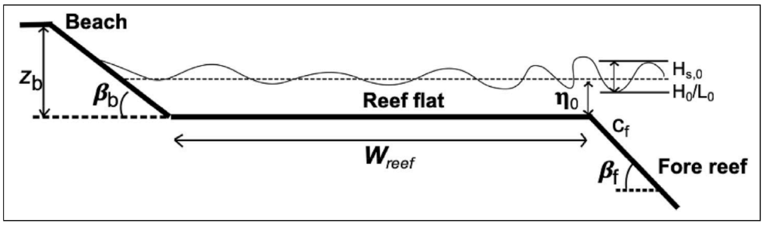


Figure 2.8: Idealized reef profile and hydrodynamic forcing parameters that HyCReWW uses as model inputs. Taken from Rueda et al. (2019)

2.3.1. Metamodel inputs

Bathymetry and topography

HyCReWW requires only a schematized reef profile represented by 4 parameters, the fore reef slope, β_f; the reef width, $W_(reef)$; the beach slope β_b; the reef friction factor and c_f.

- **Coefficient of friction,** c_f

  The roughness of the reef is represented by a single parameter, the coefficient of friction (c_f), that accounts for the wave dissipation process due to the structure of the corals and the vegetation. Wave dissipation affects wave shoaling, set up and run up. The coefficient of roughness is a highly localized dimensionless parameter that represented the dissipation of wave energy due to the interaction between the waves and reef structures. Coral reef structures are highly variable and the coefficient of friction is difficult to quantify. In comparable numerical models of wave transformation over coral reefs, c_f is a highly calibrated parameter specific to that model. Without detailed bathymetry, flow measurements, or even roughness height of the coral reef structures, it would be fruitless to assign a value for c_f. Thus, the value of this parameter is explored further in the sensitivity analysis before an input value is chosen.

- **Reef flat width,** W_r

  The width of the reef flat is estimated using Google Earth's measuring tool. The nesting beaches are mainly located on the beaches just southeast of the concrete factory. In this region, the reef width varies from about 50 to 200 m from northwest to southeast. HyCReWW's sensitivity to the reef width is explored further in the sensitivity analysis.

- **Beach slope,** B_B

  Detailed topography of the beach was unavailable. Beach slope is the only parameter needed to describe the topography. The publicly available data sets of topography were of a resolution lower than the width of the beach, and thus a beach slope could not be extracted from the data. Beach slope is another parameter explored in the sensitivity analysis in the next section.

- **Fore-reef slope,** β_r

  The fore-reef slope is estimated from the ACA bathymetry. The fore-reef slope was measured as the slope between the first two points beyond the seaward edge of the reef flat. The slope varies across the reef, but is consistently steep with slopes varying from 0.23-0.5. In the interest of understanding the how variation of the slope across the reef effects the model results, the parameter is included in the sensitivity analysis.

Hydrodynamic forcing

- **Offshore wave height, H_s and wave steepness, H_s/L_0**

  The wave data used is described in the previous section. Wave transformation modeling does not have to be implemented due the local bathymetry. Offshore of the reef flat, the bathymetry drops in a steep decline to depths up 60-70 m. This depth is sufficient to characterize all offshore waves in the wave time series as deep water waves and require no further transformation. The wave direction, however, is not accounted for in the model because the model does not resolve wave refraction. All wave conditions are included and are assumed to approach shore-normally, and thus the incident waves are overestimated. The wave steepness, H_s/L_0, was calculated using the dispersion relation for deep water: $H_s/L_0 = gH_sT^2/2\pi$.

- **Water level, WL, and proxy MSL, η_0**

  The water level is defined as the total water level above the reef flat, comprised of the tide and surge. The water level from the GTSM model is not referenced to a local datum which presents a challenge for the model input. Without knowing how the water level relates to the local height of the bathymetry, there is no reference to tie the bathymetry to the water level. To resolve this, a proxy for a local datum was used, to which the GTSM data is added to. The ACA nearshore bathymetry is derived from an annual median of satellite reflectance data. The depth over the reef flat given by the ACA bathymetry was assumed as a viable approximation for mean sea level (MSL) due to the long duration of the measurement. However, across the beach, the average depth in Ras Baridi measured in the ACA bathymetry data varies from 0.23-0.48 m, leading to a range in potential proxy MSL values. The sensitivity of this parameter is tested in the next section to see if the range of values of the proxy MSL contributes significantly to the variance of the model outputs.

Input limitations

HyCReWW was developed with input limitations shown in table 2.1. This severely limits the available wave conditions that can be run to about 15% of the total conditions available. The wave height was the most stringent limitation, as most of the wave conditions were below 1 m. HyCReWW was developed to predict high risk flood scenarios, so the input limitations reflect a focus on extreme runup events. Although limiting, for the purposes of this study the smaller runup events may have less importance for the flooding of nests. For every condition below the lower limits of the model inputs, runup is assumed to be 0 m. This allows those events to be included in the analysis of the results.

Parameter	Symbol	Units	Values
Offshore water level	η_0	m	-1 - 2
Offshore significant wave height	H_s	m	1 - 5
Offshore wave steepness	H_0/L_0	-	0.005 - 0.05
Fore reef slope	β_f	-	0.05 - 0.5
Reef flat width	W_r	m	0 - 1500
Beach slope	β_b	-	0.05 - 0.5
Coefficient of friction	c_f	-	0.01 - 0.1

Table 2.1: The HyCReWW metamodel input limitations. Note that wave period is implicitly included in the wave steepness parameter.

2.3.2. Sensitivity Analysis

HyCReWW requires a simplified set of input parameters shown in figure 2.8. W_r, β_b, β_r, and c_f are each be represented by a range of values because of the uncertainty of their exact values. The time-varying hydrodynamic inputs(H_s, H_s/L_0, and WL) also contain uncertainty but it is impractical to run a range of values for each condition for 40 years. A sensitivity analysis (SA) is a strategy for understanding the effect of uncertainty in the input parameters on the model output. By understanding this, the importance of the accuracy of the input parameters can be quantified (Saltelli, 1999; Saltelli et al., 2008). For future studies in low-data environments and similar hydrodynamics, it will be possible to know which data should be sought with higher resolution and accuracy. If the range of possible values for a parameter is high, but the parameter has a negligible of the outputs compared to the overall accuracy of the model, then it is not necessary to seek better data. If the converse is true, then higher resolution data should be sought if possible.

The SA is also used to screen the parameters to decrease the amount of simulations that are run. A single simulation in HyCreWW of the entire 40-year study period can take 20 hours of computational time. The parameters that are highly sensitive are investigated in the final results by running full simulations and varying one parameter at a time, giving a distribution of runup values for a single hydrodynamic condition. Parameters whose effects are assumed negligible will be held constant when running a full 40-year simulation.

Overview

There are different methods of conducting a SA which can be grouped into two classes, local and global. A local SA is assessing the sensitivity of a parameter within a specific region of interest, like a base point or specific parameter values (Saltelli et al., 2004), otherwise known as a ”one at a time” (OAT) method. For complex models with large numbers of inputs, screening exercises can be implemented to find the most important parameters to further analyse, fixing the parameters of lessor importance. Global sensitivity analyses consider the variations and interactions of parameters over their entire ranges to understand how different parameter combinations influence the model output, often focusing on the variance of the model outputs such as the method of Sobol. According to Saltelli et al. (2004), the properties that make up a robust SA are:

1. The ability to handle scale and shape of parameter distributions such that sampling represents the distributions.
2. Multidimensional averaging, where the effect of one factor is assessed while all the others are varying.
3. Model independence, such that nonlinearity and non-additivity between parameters is respected. Non-additivity is defined as two parameters’ combined effects being different than the sum of their individual effects.
4. Ability to group factors as single factors for easy analysis of results.

Variance based methods have proven effective in meeting these requirements (Saltelli, 2002, 1999; Borgonovo, 2007), but they assume that model parameters are independent. This presents a problem in the use of a sensitivity analysis on a runup model, as the parameters of wave height, steepness and water level can be dependent upon one another. Methods for handling correlated inputs’ use in variance based methods have been proposed by Saltelli et al. (2004). Despite this, variance based methods rely solely on variance of the outputs to describe the sensitivity of parameters and thus may be insufficient (Saltelli et al., 2004; Borgonovo, 2007). Borgonovo (2007) presents another indicator, δ which is moment independent and therefore considers the entire distribution of outputs and inputs. δ is also able to handle correlations between inputs and outputs.

Borgonovo's method

The moment independent δ is defined using the unconditional density/cumulative distribution, $f_Y(y)/F_Y(y)$ of the model outputs, $Y_{1,2,3,..,n}$, given by the input parameters, $X_{1,2,3,..,n}$, which vary in their uncertainty ranges. By fixing one of the inputs X_i at a value x_i^*, the shift between $f_Y(y)$ and $f_{Y|X_i}(y)$ is given by:

$$s(X_i) = \int |f_Y(y) - f_{Y|X_i}(y)|\, dx \tag{2.1}$$

The expectation of the $s(X_i)$ is then given by:

$$E_{X_i}[s(X_i)] = \int f_{X_i}(x_i)[\int |f_Y(y) - f_{Y|X_i}(y)|\, dx]\ dx_i \tag{2.2}$$

and the moment independent sensitivity indicator,δ_i, is defined as:

$$\delta_i = \frac{1}{2}E_{X_i}[s(X_i)] \tag{2.3}$$

As an sensitivity indicator, Borgonovo states that ”δ_i represents the normalized expected shift in the distribution of Y provoked by X_i.” The properties of δ_i are shown in table 2.2. Proofs of each of the properties can be found in detail in Borgonovo, 2007. δ has been shown to agree with variance based methods in ranking less important parameters, but varies in ranking more important parameters. This proves that contributions to output variance are not sufficient to indicate the sensitivity of a parameter to the entire range of output distribution (Borgonovo, 2007). There is still value in using variance-based indicators to gain insight into which parameters most influence output variance. For that reason, both δ and a variance-based first-order sensitivity index, S_1, computed using the Sobol method are used to get the most comprehensive understanding of the effects of parameter uncertainty.

Property	Meaning
$0 \leq \delta_i \leq 1$	Bounds the possible values δ_i can assume
δ_i = 0	If Y is independent of X_i then δ = 0
$\delta_{1,2,3,..,n}$ = 1	All parameters are equally important

Table 2.2: Properties of δ from Borgonovo (2007). See reference for proofs of properties.

In order to calculate δ, each parameter must be sampled from the ranges of their uncertainty. The ranges for the parameters used in the sensitivity analysis are shown in table 2.3. The goal in choosing parameter ranges is to sample the parameter space in a way that accurately depicts the actual parameter space. Data was only available for the hydrodynamics, and there was no information available on the local ranges of the parameters. Thus, assumptions were made for the ranges of the fore reef slope, reef flat width, beach slope and coefficient of friction parameter ranges that are shown in 2.3. The beach slope was taken as the range within the model limits of beach slopes from 0.01 to 0.1. The model range was also used as the range of values for inputs of c_f, from 0.01 to 0.1. This is in line with the range of values used in other studies (Pearson, 2016). The model limits of fore-reef slope were calculated by estimating the slope across four bathymetry profiles pulled from the Allen Coral Atlas in Ras Baridi. The minimum and maximum slopes estimated (0.23 and 0.50) are used as the parameter range. The reef flat width in Ras Baridi ranges from about 50 to 200 m measured by Google Earth's measuring tool on the visible reef flat, and is used as the parameter range.

Parameter	Symbol	Units	Values
Offshore water level	WL	m	-0.05 - 0.83
Offshore significant wave height	H_s	m	1 - 3.75
Fore reef slope	β_f	-	0.23 - 0.5
Reef flat width	W_r	m	50 - 250
Beach slope	β_b	-	0.01 - 0.1
Coefficient of friction	c_f	-	0.01 - 0.1
Proxy MSL	η_0	m	0.27 - 0.48

Table 2.3: The sensitivity analysis parameter ranges HyCReWW metamodel input limitations. Note that wave period is implicitly included in the wave steepness parameter.

The sampling method used is Latin hypercube sampling (LHS) which is designed to provide more efficient and representative sampling compared to random sampling. LHS divides the parameter space into equal intervals and samples one value from each interval. The input parameters,η_0, H_0 and H_0/L_0 have distributions that are not uniform, unlike β_f,W_{reef}, β_b, and c_f. For this reason, the 4000 sample sets of η_0, H_0 and H_0/L_0 had to be manually filtered to match the entire distribution of those parameters. The resulting 2511 sets are shown in figure 2.9. Note that the WL in figure 2.9 has the sample proxy MSL added to it for each point.

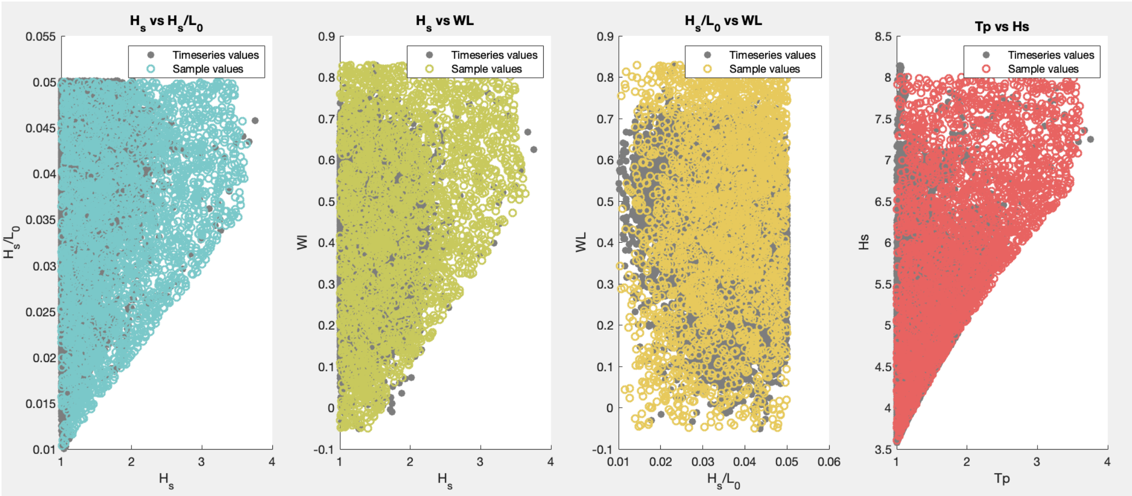


Figure 2.9: Scatter plots of the 2511 sample values (colored points) generated using latin hypercube sampling plotted against the entire set of data (grey points) that are valid inputs for HyCReWW. WL in this figure is comprised of the GTSM water level and the sample value of the proxy MSL.

2.4. BEWARE 2.0 metamodel

2.4.1. Metamodel description

Bayesian Estimator for Wave Attack in Reef Environments 2.0 (BEWARE 2.0) establishes a connection between hydrodynamics and coral reef geomorphology to better understand and assess coastal flooding risks along reef-lined coasts, as indicated by Pearson et al. (2017). This approach involves the development of a synthetic database of runup data through the utilization of XBeach 1D non-hydrostatic simulations and representative cluster profiles (RCPs), which cover a spectrum of hydrodynamic conditions.

BEWARE 2.0 distinguishes itself from HyCReWW by employing pre-existing RCPs that have undergone runup estimations modeled in XBNH across a range of wave scenarios. It is also different from HyCReWW in that it uses real measured bathymetry in its database (Scott et al., 2020). The metamodel operates in two main steps. In the initial step, the input profile is matched against a set of 530 RCPs. The 530 RCPs were already set into 175 groups that share comparable morphology and hydrodynamics. Each of the 175 groups of profiles is represented by 1 profile. The subsequent step links the first match to the 530 profiles to the 175 representative profiles. The runup value is extracted for the given hydrodynamic input state. This is repeated for each BEWARE 2.0 profile that the input profile was matched to and an ensemble runup value is generated. The calculation of the final ensemble runup value involves weighing the runup values corresponding to each RCP match by their associated matching probabilities.

2.4.2. Metamodel inputs

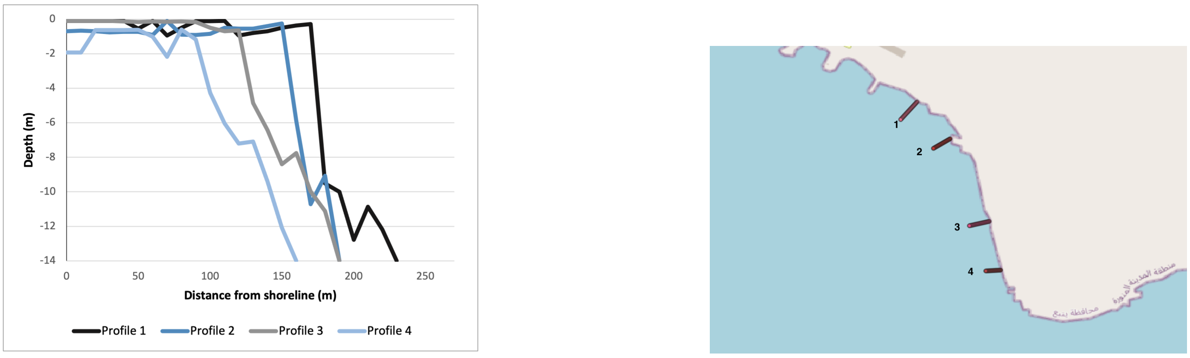
The inputs to the BEWARE 2.0 are similar to HyCReWW. The hydrodynamic input conditions are offshore wave height, wave period, and water level. For consistency in comparison, the same hydrodynamics are used as described in section 2.3.1. The bathymetry is specified by an input profile, while the beach is described by a single beach slope parameter, β_b, like HyCReWW. The roughness of the reef is described by a constant coefficient of roughness, c_f. The value of roughness in the metamodel is set to 0.05, and the beach slope is set to 0.1. These are default values and currently cannot be altered in BEWARE 2.0.

BEWARE 2.0 was designed to evaluate runup primarily for extreme flood events and has input limitations that restrict the hydrodynamics conditions to only the highest 0.5% of conditions in the 40-year timeseries. The input restrictions are shown in table 2.4. Wave period was the most restrictive input for BEWARE 2.0.

Parameter	Symbol	Units	Values
Offshore water level	η_0	m	0 - 4
Offshore significant wave height	H_s	m	1 - 11
Wave period	T_p	s	6 - 22
Coefficient of friction	c_f	-	0.01 - 0.1

Table 2.4: The BEWARE 2.0 metamodel input limitations.

To capture the variation in reef flat width's effects on runup levels, 4 profiles were extracted from the Allen Coral Atlas bathymetry. Profiles 1-4 have reef flat widths of 170, 150, 120 and 80 m, respectively, as shown in figure 2.10. The profile orientation changes across the beach, leaving the southeastern side of the beach more exposed to the dominant wave direction out of the northwest. The southeastern side of the beach where profiles 3 and 4 are located is slightly less sheltered than profiles 1 and 2. Waves approaching from the northwest are have to refract less at profiles 3 and 4 than at profiles 1 and 2. Because BEWARE 2.0 is based on XBeach 1D with directional spreading not included, refraction and the difference in profile orientation is not taken into account.



(a) (b)

Figure 2.10: (a) The four profiles extracted from the ACA and (b)their corresponding locations in Ras Baridi.

2.5. Assessment of model results

2.5.1. Ras Baridi: Full timeseries 1978-2018

The 10-meter resolution bathymetry data from the Allen Coral Atlas for Ras Baridi was used to run BEWARE 2.0 and HyCReWW. This involved utilizing the 40-year hydrodynamic datasets to model runup estimations comprised of the water levels and waves described in sections 2.3.1and 2.4.2. Due to BEWARE 2.0's limitations with input parameters, it could only run it for 1088 conditions, compared to HyCReWW's 50,000 conditions. To ensure consistency in return period calculations for each model, comparisons of the outputs were from the same conditions. All other runup values from HyCReWW were set to 0. The goal is to assess the likelihood of sea turtle nest inundation as a function of beach elevation. To achieve this, the runup results from the metamodels were analyzed using their return periods, which are described in the next section.

Return periods

The empirical return periods were calculated using the peak-over-threshold (POT) method, a statistical approach that is useful in quantifying extreme events. First, the threshold needs to be defined, which is an arbitrary value that describes a 'minimum extreme event'. In this case, finding the likelihood of sea turtle nest inundation is the goal, so any nest flooding is considered extreme. An appropriate threshold would be the minimum nesting elevation, however, there were no measurements of nest elevation for the beaches of Ras Baridi. As described in chapter 1, a common method of nest relocation is to move nests above the visible high tide line. The question of how far should the nest be moved can be answered by knowing the likelihood of flooding beyond the high tide line or mean high water (MHW). The MHW from the GTSM data including surge for 1979-2018 was 0.2 m. This will be used as the threshold to define an 'extreme' event for Ras Baridi. It is clear that the runup associated with the wave conditions that are included in the metamodels are likely to surpass the 0.2 m threshold. Indeed, because of the strict input limitations on the models and the mild wave climate of Ras Baridi, the conditions run by the models are already quite extreme. They occupy the highest 15% and 0.5% of events in the time series for HyCReWW and BEWARE 2.0, respectively. The effects of selecting the MHW as a threshold are shown in chapter 3.

After a threshold is defined, the values above the threshold, or peaks, are extracted. However, the interest is in the peak runup during a storm event. The storm duration for the Ras Baridi was chosen as 48 hours after testing different values. Storm durations longer than 48 hours did not significantly change the number of peaks, while lower storm durations led to a large numbers of peaks, implying that the peaks were from the same storm events. The number of storms per year, N_s, is estimated by dividing the total number of peaks by the number of years (in this case, 40). The exceedance probabilities, Q_i are calculated for each event, and the return periods are then given by:

$$RP = \frac{1}{QN_s} \tag{2.4}$$

2.5.2. Methodological validation

The lack in of in-situ measurements prevent the validation of the model results. However, the novelty of the methods used provide impetus that they be validated to ensure their appropriateness, accuracy, and reliability in addressing the research objectives. Specifically, The suitability of the metamodels in a low-data environment to model runup is verified by assessing the metamodel performance with low-resolution bathymetry.

The methodological validation was made possible by using validation data that BEWARE 2.0 was developed with. BEWARE 2.0 was originally validated against a XBeach 1D NH+ model using 6 locally measured, <5m resolution bathymetry profiles at different coral reef fronted coastlines around the world. The XBeach model was previously validated against measurements of waves and water levels at the shoreline for these particular sites. To ensure that BEWARE 2.0 is able to handle low-resolution bathymetry data, the six reef profiles that were used for the validation of BEWARE 2.0 were extracted at the same locations from the Allen Coral Atlas in Funafuti, Tuvalu; Molokai, Hawaii; Molukeia, Hawaii; Roi Namur, USMI; Ipan, Guam and Ningaloo reef, Australia. The locations were estimated from the images and figures in the literature describing each field campaign (Filipot and Cheung, 2012; Pequignet et al., 2011; Storlazzi et al., 2004; Becker et al., 2012; Beetham et al., 2016; Van Dongeren et al., 2013). The profiles extracted from the ACA are plotted against the high resolution profiles in 2.11.

The ACA bathymetry is much less accurate in depths greater than 10 m (Li et al., 2019), and for each profile would reach a maximum depth where it would plateau. This is a limitation of the ACA's methods in generating bathymetry data, which was not intended for use other than in the nearshore (Li et al., 2021). Each profile was cut off at the point where the bathymetry would plateau, which varies from about 10-20 m. For the sake of matching the high resolution profiles in the model, the low resolution profiles were extended to 30 m depth using the the average slope from the reef flat edge to the seaward extent of the data. Runup for these 'validation profiles' was previously modeled in XBeach and BEWARE 2.0 for 12 input conditions shown in table 2.5.

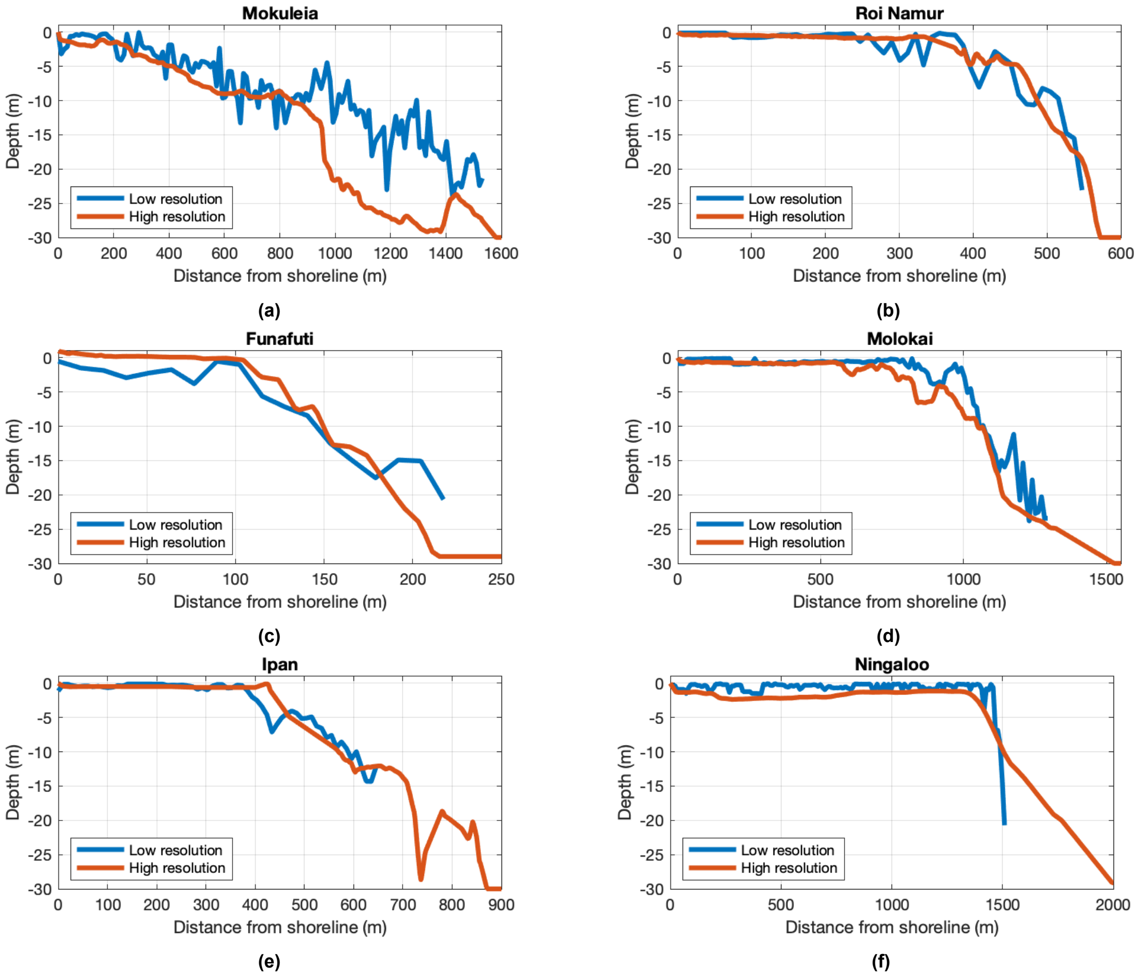


Figure 2.11: Plots (a) through (f) show the ACA 'low resolution' profiles (blue) vs. the 'high resolution' profiles (orange) for each location.

$WL(m)$	$H_s(m)$	$T_p(s)$	β_b	c_f
0	1	8	0.1	0.05
0	3	8	0.1	0.05
0	3	16	0.1	0.05
0	5	8	0.1	0.05
0	5	16	0.1	0.05
0	7	16	0.1	0.05
1	1	8	0.1	0.05
1	3	8	0.1	0.05
1	3	16	0.1	0.05
1	5	8	0.1	0.05
1	5	16	0.1	0.05
1	7	16	0.1	0.05

Table 2.5: The model inputs conditions used in validating BEWARE 2.0.

To assess the performance of the metamodel, the results need to be compared to the same baseline. The baseline should also represent reality, which would ideally be measured runup values in Ras Baridi. As measured runup for Ras Baridi was not available, the metamodel results were compared to the results of validated XBeach models for each of the 6 validation profiles. For this study, the conditions in table 2.5 were run in XBeach, BEWARE 2.0 and HyCReWW using both the high resolution and low resolution bathymetry profiles. 10 of the 12 conditions were valid to run in HyCReWW. The conditions with 7 m H_s have wave heights that are above the 5 m limit for the metamodel, so only the results of those 10 conditions are compared for the performance metrics.

Results of the comparisons to the baseline are evaluated based on the root-mean-square error (RMSE), bias, the relative bias (RB) and scatter index (SI). Together these 4 indicators provide a comprehensive understanding of model performance.

Bias measures the systematic overestimation or underestimation of model data compared to measured data. It is calculated as the average difference between model and measured values and provides insight into the overall accuracy of the model. In this case, the modeled values are from the metamodel, and the measured values are from XBeach. A significant bias indicates that the model consistently over- or under-predicts, which can affect the model's usefulness and reliability.

Relative bias is a normalized version of bias, calculated as the bias divided by the mean of the measured data (Van Der Westhuysen, 2010):

$$RB = \frac{\sum_{i=1}^{n}(x_{i,metamodel} - x_{i,XBeach})}{\sum_{i=1}^{n} x_{i,XBeach}} \tag{2.5}$$

where $x_{i,BEWARE}$ and $x_{i,XBeach}$ are the results of runup for BEWARE 2.0 and XBeach, respectively. It provides a relative measure of the bias with respect to the scale of the measured data. Relative bias allows for a standardized comparison of bias across different datasets with varying scales and helps assess whether the model's bias is proportionally significant relative to the variability in the observed data.

RMSE quantifies the magnitude of errors between model and measured data. It is calculated as the square root of the mean of the squared differences between model and observed values and provides a measure of the overall model-data agreement while considering both bias and scatter. A lower RMSE indicates a better fit between the model and measured data and helps it identify regions where the model performs poorly.

Scatter index measures the relative spread or variability of model data around the measured data. It is calculated as the standard deviation of the model values divided by the standard deviation of the measured values (Van Der Westhuysen, 2010):

$$SI = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{i,metamodel} - x_{i,XBeach})^2}}{\frac{1}{n}\sum_{i=1}^{n} x_{i,XBeach}} \tag{2.6}$$

SI assesses how well the model captures the variability and patterns present in the measured data. A lower SI indicates that the model reproduces the observed variability more accurately, while high SI values suggest that the model underestimates variability.

The performance metrics for each profile were were calculated by making three different comparisons using the hydrodynamics in table 2.5 as model inputs:

- 'High resolution case:' XBeach compared to both HyCReWW and BEWARE 2.0 using the high-resolution validation profiles.
- 'Low resolution case: XBeach using high-resolution bathymetry compared to both HyCReWW and BEWARE 2.0 using low-resolution bathymetry
- 'XBeach case:' XBeach using the high- and low-resolution validation profiles.

To evaluate the performance of the metamodels in the context of low-resolution bathymetry, a comparative analysis was conducted between two sets of performance metrics: the low and high resolution cases. These cases were chosen for comparison because they share a common baseline condition—a validated XBeach model that uses high resolution bathymetry. By examining their performance differences under low-resolution bathymetry, which metamodel excels can be identified in this challenging scenario.

Furthermore, the extent of accuracy loss in the metamodels was assessed when employing low-resolution bathymetry. To assess the impact of using a low-resolution profile for database matching, XBeach was run using high- and low-resolution bathymetry and the results were compared using performance metrics.

In essence, these comparative analyses offer valuable insights into the metamodels' performance under conditions of reduced data resolution. They help identify which metamodels are robust in handling low-resolution bathymetry and shed light on the implications of such reductions in data precision on accuracy when integrating them into modeling frameworks.

3

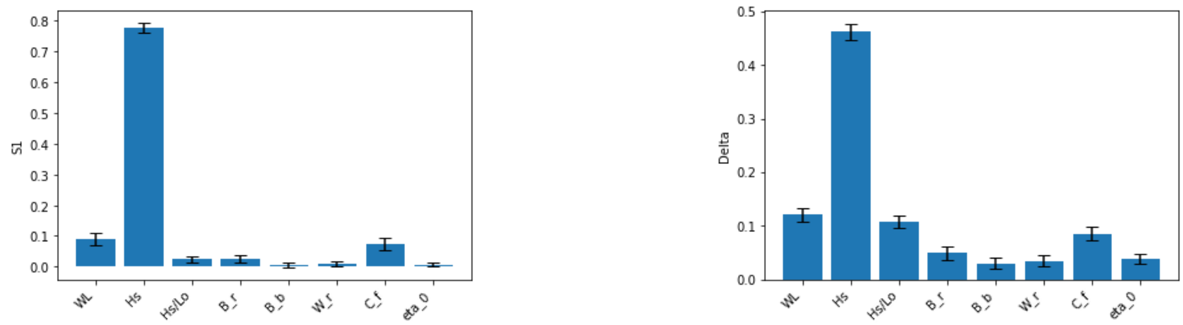
Results

In this section the results of the metamodels HyCReWW and BEWARE 2.0 in Ras Baridi are presented. The results of the metamodel performance are also presented for the validation profiles.

3.1. HyCReWW Results in Ras Baridi

3.1.1. Sensitivity analysis results

Using the 2511 sets of model inputs generated with LHS, Borgonovo's delta, δ, and the first order sensitivity index, S_1, are calculated and shown in the figures 3.1b and 3.1a. The most important parameters ranked in decreasing order as shown by the δ values are H_s, WL, H_s/L_0 and c_f. These results are in agreement with S_1, with the exception of H_s/L_0 which is lower than c_f. The difference in values between S_1 and δ is pronounced for H_s, β_b, W_r, and η_0. H_s has a larger effect on the variance of the outputs than it does the total distribution of the outputs, whereas β_b, W_r, and η_0 have a smaller effect on the variance of the outputs than they do the total distribution of the outputs.



(a) (b)

Figure 3.1: (a) S_i values and their 95% confidence intervals for each of the 8 parameters used in the model for 2511 sample sets and (b) δ values and their 95% confidence intervals for each of the 8 parameters used in the model for 2511 sample sets.

Parameter selection for HyCReWW input screening

Based on the sensitivity analysis results, the parameters that were selected to be fixed inputs for HyCReWW the full 40-year simulation were the proxy MSL, η_0, the beach slope, β_b, the reef width, W_r, and the reef slope, β_r. In the full simulation, WL, H_s/L_0 and H_s were allowed to vary according to their time series. The following paragraphs discuss how the values were chosen for each parameter.
]

- **Proxy MSL,** η_0

  The proxy MSL ranked 3rd to last and 2nd to last in importance for δ and S_1, respectively, likely due to the fact that it's range was a third of that of the water level. In the metamodel, η_0 is simply added to the water level, so it's effect was only a fraction of that of the water level. The average value of η_0 across the reef flats of the four profiles was 0.42 m, and was used as the input to be added to the water level time series. The water level is then referenced to the proxy MSL.

- **Beach slope, β_b**

  There was no readily available data of the beach topography to measure or estimate beach slope, however beach slope has been shown to be correlated to grain size (Bujan et al., 2019). In meta-analysis of 2144 different measurements of beach slope and their associated grain size, Bujan et al. (2019) present a power-law fit to the data:

$$tan(\beta_b) = a(D_{50} - 0.125)^b + c \tag{3.1}$$

  where $a = -0.154$, $b = -0.145$, and $c = 0.268$. The D_{50} of each of the 3 sediment samples described in section 2.2.4 were used in the formula to get an average value of the beach slope of 0.085. This value was used as the beach slope for HyCReWW model input.

- **Coefficient of friction, c_f**

  c_f was at the highest position of influence of the five temporally constant parameters, 2-10 times as important as the others in both δ and S_1 . In order to explore the effects of the uncertainty of c_f further, the 40-year simulation will be run for 10 different c_f values.

- **Reef slope, β_r**

  The reef slopes for of the 4 profiles extracted from the ACA bathymetry data used in HyCReWW and BEWARE 2.0 were taken as the estimated value of their slope from the edge of the reef flat to the first data point past that. The data is 10 m resolution, so it may be that the slope estimation is missing part of the curve of the reef as the reef flat ends. The accuracy of the data drops sharply after 10 m (Li et al., 2021), so only the slope is only estimated from the first 10 m of fore-reef. The slopes estimated for each of the four profiles shown in figure 2.10 are 0.31, 0.42, 0.50, and 0.46, respectively.

3.1.2. HyCReWW simulation results

The SA showed that results of HyCReWW were sensitive to the reef width, W_R, and the coefficient of friction, c_f. Those sensitivities were explored further by running the full time series for each of the four profiles that have different reef widths for 10 values of c_f from 0.01 to 0.1. All other results were set to 0 m of runup. The results of the peak over threshold method (POT) for profile 3 with a reef width of 170 m and a c_f of 0.05 are shown in figure 3.2. A threshold of 0.2 m corresponding to MHW was used with a de-clustering time of 48 hours between peaks. The input restrictions on HyCReWW resulted in a minimum value of 0.48 m of runup, rendering the selection of a low threshold inconsequential. HyCReWW's input restrictions weeded out the most extreme events, with only 15% of events being modeled. Had HyCReWW been able to model the waves below 1 m, it is likely that the other 85% of runup results would have fallen below 0.48 m. It is possible that this would have caused the threshold to be too low to be a statistical extreme. In that case, a different physical value would prove a better threshold, such as mean higher-high water, the highest astronomical tide, or mean nesting elevation. In this case, the chosen threshold remains sufficient because of HyCReWW's input restrictions.

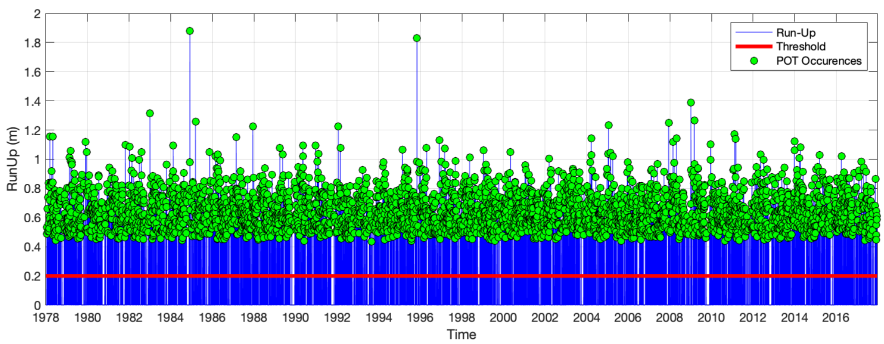


Figure 3.2: POT results for c_f of 0.05 and a reef width of 170 m. The horizontal red line denotes the threshold value of 0.2 m. The lines plot all the events and the green dots are the selected peaks above the threshold for the 48 hour de-clustering time.

The variation of the results are illustrated with two figures, 3.3 and 3.4, displaying the return periods of different values of runup for: a constant c_f and varying widths and for a constant W_r and varying c_f. The runup for different return periods and varying reef widths for the 40 years are shown in figure 3.4. The results showed a slight decrease in runup for increasing reef width, meaning lower values of runup for the same return periods as W_r increases. The results for varying c_f in figure 3.3 on a constant reef width had a similar, but more pronounced effect on runup. Increasing c_f in the model lowered runup values, which in turn lowered runup values for the same return periods as c_f decreased. The upper right area of each figure shows about a 0.5 m jump in runup for the events with return periods of 20 and 40 years. These events correspond to the two largest storm events in the 40-year period in 1985 and 1996, respectively, The wave heights associated with these events were 3.75 m and 3.27 m. These events are clearly visible in figure 3.2. These events are outliers, with values about 0.5 above the next highest peak.

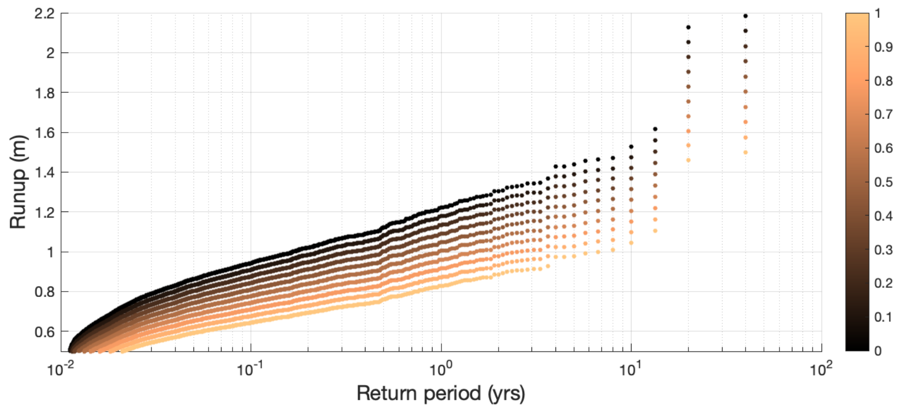


Figure 3.3: Plot showing the results of HyCReWW for all dates between 1978 to 2018 for profile 2 with a reef width of 150 m. The runup level in meters is shown against and return period for 10 different values of c_f from 0.01-0.1.

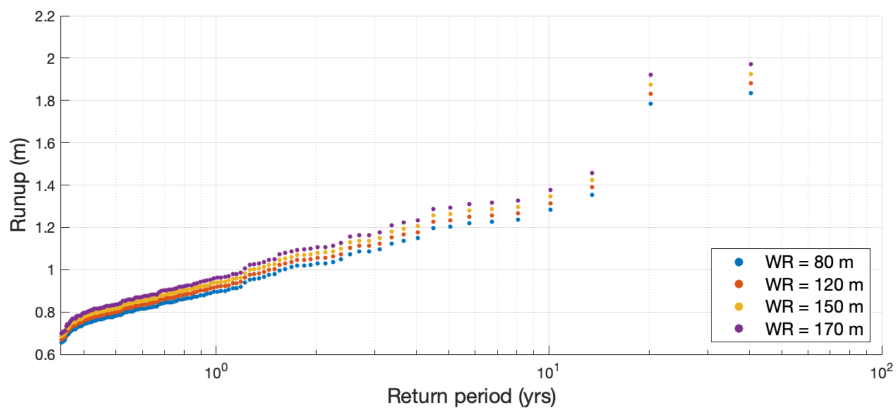


Figure 3.4: Plot showing the results of HyCReWW in Ras Baridi for all dates between 1978 to 2018 for the 4 different profiles. The flood level in meters is shown against the reef width and return period.

Table 3.1 shows the median runup values for different return periods across the beach, as well as their ranges due to the different c_f values. Note that the interval between the four values of each return period for each return period across all profiles was constant. The values in the table were rounded, so the some of the differences between values seen in figure 3.4 are not noticeable. The figures 3.3 and 3.4, as well as table 3.1 illustrate that as the return period increases, there is a notable increase in the range of runup values from near 0.15 to about 0.4 m. This suggests that when dealing with larger waves and water levels, the uncertainty in predicting runup with respect to parameters c_f and W_r also increases. To narrow down this uncertainty, it is imperative to validate these results using actual runup data. The growth of the differences between runup for a given return period across different values of

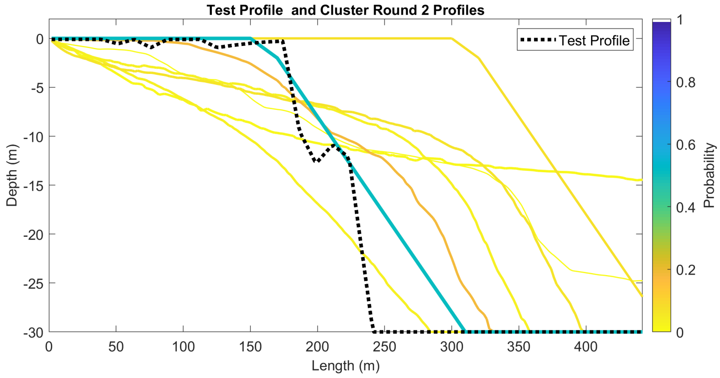
c_f and W_r is nearly linear. As the range of results widens, the difference in runup remains consistently uniform for a given return period. This consistency implies that the interpolation method maintains a linear relationship between runup and varying values of reef width and friction coefficient for each specific return period. In essence, while the spread in runup values expands with increasing return periods, the relationship between runup and the parameters c_f and W_r remains linear and uniform within each return period.

$RP(yrs)$	$W_r = 80m$	$W_r = 120m$	$W_r = 150m$	$W_r = 170m$	Variation (m)
1	0.95	0.95	0.9	0.9	$\pm$ 0.15
5	1.3	1.25	1.2	1.2	$\pm$ 0.2
10	1.4	1.35	1.3	1.3	$\pm$ 025
20	1.9	1.9	1.85	1.75	$\pm$ 0.3
40	1.95	1.95	1.9	1.9	$\pm$ 0.4

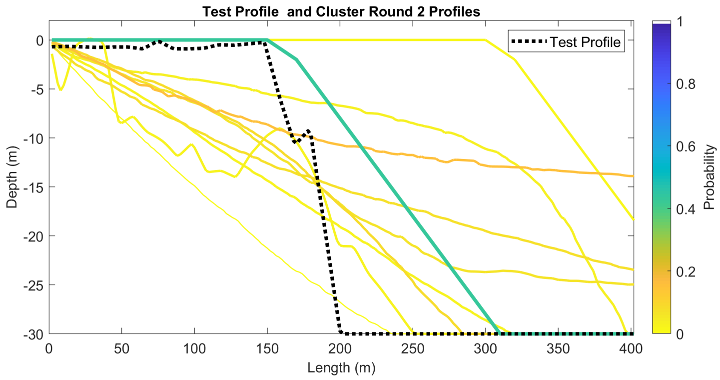
Table 3.1: Runup values from HyCReWW for different reef widths and return periods. All values were rounded to the nearest 0.05 m. The range due to variation in c_f is also included in the last column.

3.2. BEWARE 2.0 Results in Ras Baridi

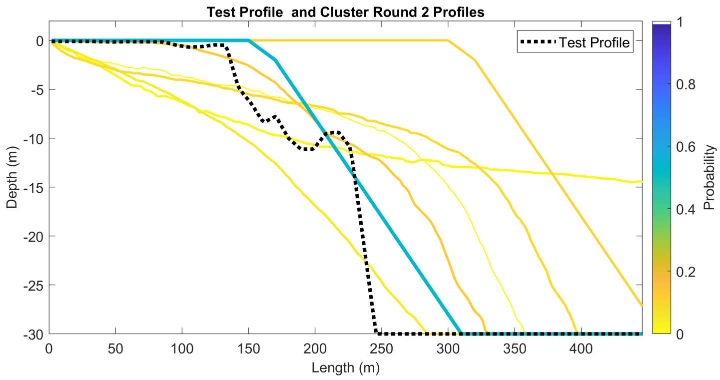
The 2nd round of profile matching for the four profiles in Ras Baridi is shown in figure 3.5. Both profiles 1, 2 and 3 matched to the same profile with the highest likelihood, so the values of runup for these profiles were very similar. In profiles 1 and 3, all of the matched profiles were the same, just with slightly different matching likelihoods. This difference in the profile matching likelihoods appears to have resulted in a slight difference in runup. Profile 2 had a more diverse profile match, amongst the lower likelihood matches than profiles 1 and 3, but still shared some similarities in the matched profiles. Despite the the matching being almost identical between profiles 1 and 3, profiles 1 and 2 had much more similar runup results. Profile 4 matched to profiles with much lower reef widths.



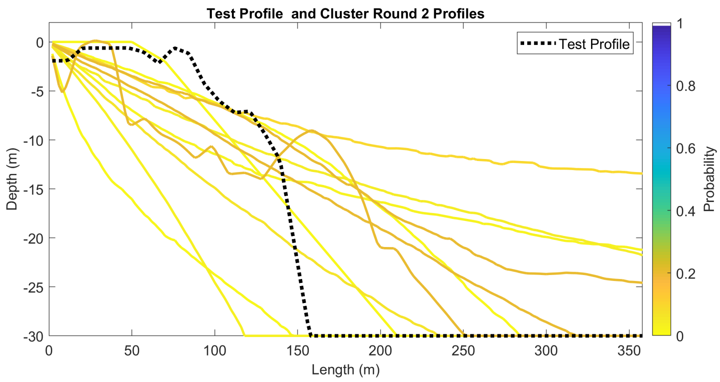
(a) Profile 1, W_r = 170 m



(b) Profile 2, W_r = 150 m



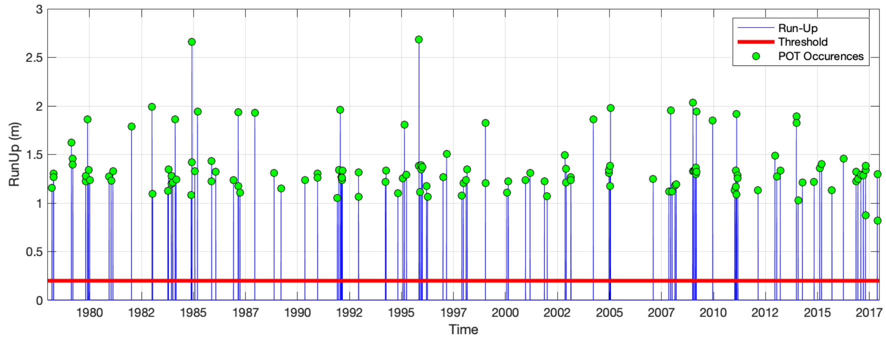
(c) Profile 3, W_r = 120 m



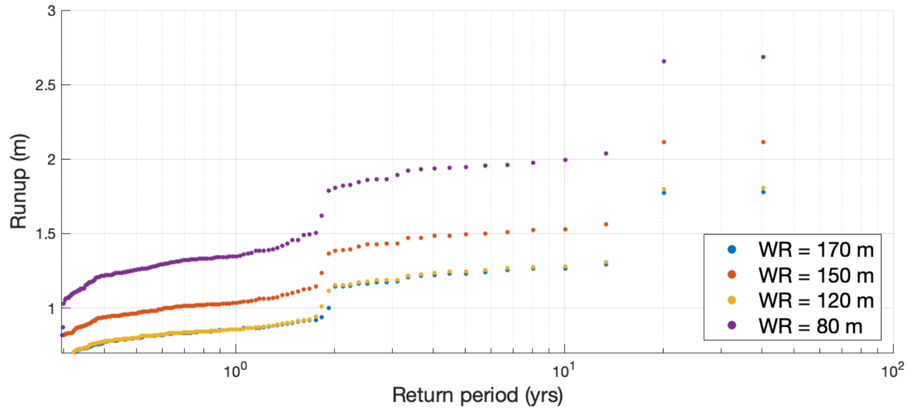
(d) Profile 4, W_r = 80 m

Figure 3.5: The results of the second round of profile matching in BEWARE 2.0 for each of the profiles in Ras Baridi. Profiles 1, 2, 3, and 4 are shown in figures (a),(b),(c), and (d), respectively. The original profile from the ACA is shown as a dashed line, and the matched profiles with color-coded by their likelihood of matching are also plotted.

The results of running the 40-year timeseries of waves and water levels for the 4 profiles across the beach at Ras Baridi are shown in figures 3.6a, 3.6b, and table 3.2. Figure 3.6a shows the results of the POT method for a threshold of 0.6 m. In figure 3.6a, the threshold was low enough that all of the 1088 events that had runup values greater than zero were included. The minimum runup value of the 1088 events was 0.61 m.



(a)



(b)

Figure 3.6: (a) POT results for c_f of 0.05 and a reef width of 150 m. The horizontal red line denotes the threshold value of 0.2 m. The lines plot all the events and the green dots are the selected peaks above the threshold for the 48 hour de-clustering time and (b) The runup results of BEWARE 2.0 from 1978-2018 for each of the 4 profiles are plotted in different colors against their return periods. Each profile had a c_f value of 0.05

As shown in figure 3.6b, there are two steps in the runup at return periods 1.5 years and 20 years. These jumps correspond neatly with the three bands of runup values in figure 3.6a. These bands are not apparent in the runup results of HyCReWW, but were apparent in the wave conditions that corresponded to the peak runup values, shown in figure 3.7. In the top panel of figure 3.7 where H_s is plotted, the 3 steps seen in figure 3.6b are clearly shown. In the lower panel where T_p is shown, the bands of data are not clear, indicating that the steps in figure 3.6b occurred because of the pattern of H_s. The question of why this step-function plot did not appear in the HyCReWW data can then be answered by the difference in input limitations in BEWARE 2.0 and HyCReWW. The limitation of $T_p \geq$ 6 s in BEWARE 2.0 caused the 3 bands of H_s to emerge.

Figure 3.7: Values of H_s and T_p that correspond to the peak runup values are shown. H_s and T_p are color coded with the corresponding bands of the return periods of runup. Orange corresponds to 0-1.5 years, blue to 1.5-20 years, and red to 20-40 years.

In figure 3.6b increasing return period, the range of runup values increased for varying W_r from about 0.5 m to about 0.9 m in a fairly linear fashion. The difference in runup for a given return period across the 4 reef widths was strongly nonlinear, with the runup sharply increasing for decreasing reef width. There is almost no difference (<0.05 m) in runup between the profiles with reef widths of 150 m and 200 m, which can be partially explained by the profiles' highest likelihood profile match being the same. It is unclear why profile 3, with a reef width of 100 m, does not also have a similar runup value despite matching the same profiles.

The values of runup for RPs 1, 5 10, 20 and 40 are shown in table 3.2. They highlight the range of runup values across the beach for more extreme events. BEWARE's sensitivity to reef width is also correlated with it's profile matching. Profile 4 with a reef width of 50 m had the largest values of runup, and matched with profiles with a smaller reef width as seen in figure 3.5. This difference in profile matching helps explain the differences in runup for a given return period, and it highlights the influence that the profile matching process has on the model results. In this case, the differences in reef characteristics (reef width and fore-reef slope) between the actual and the matched profiles reef width effect the runup results.

$RP(yrs)$	$W_r = 80m$	$W_r = 120m$	$W_r = 150m$	$W_r = 170m$
1	1.35	1	0.85	0.85
5	1.75	1.5	1.25	1.25
10	2	1.5	1.3	1.3
20	2.65	2.1	1.8	1.8
40	2.7	2.1	1.8	1.8

Table 3.2: Runup values from BEWARE 2.0 for different reef widths and return periods. All values were rounded to the nearest 0.05 m.

3.3. Impact on turtle nests

The time series of runup from each of the models also provide information about the duration of nest inundation. The inundation of green sea turtle eggs for a period of 1 or 3 hours has been shown to reduce egg viability by less than 10%, and inundation for 6 hours by about 30% (Pike et al., 2015). In Ras Baridi, the severity of the repeated overwashing of nests by wave runup is dependent on the duration of the inundation. The distributions of the duration of wave runup events above a certain threshold value were investigated to better understand the risk that nests face. The following sections investigate the duration of swell events and runup heights for the HyCReWW and BEWARE 2.0 runup results.

The goal was to explore if the duration of inundation was correlated to runup height, so that nests could be relocated to elevations where they would be safe from flooding for long periods of time. The durations of swell events were defined by consecutive runup events. The minimum value of the runup modeled with HyCReWW was 0.48 m, so the events are consecutuve events with runup height greater than or equal to 0.48 m. Empirical probability density functions (PDFs) were created for the durations of inundation events, and log-normal PDFs were fitted to them for the purpose of extracting statistics.

3.3.1. Flood durations with HyCReWW results

First, the duration a swell event was plotted against the average runup during the swell to assess whether the wave runup height was correlated to the storm duration, shown in figure 3.8. Each point is colored coded by its empirical PDF value based on the probability of the runup occurring.

In figure 3.8, there was a higher probability of short duration events for small runup. This is partially a function of the duration of smaller runup events getting cut off by the input restrictions of HyCReWW. It is probable that the smaller runup events would be distributed more evenly for higher durations if all wave conditions were run in the model. At around 0.7 m, the duration starts to increase with runup away from 0 hours of duration, but on the whole, the average runup height was not very well correlated to inundation,

It is clear from 3.8 that moving a nest to a higher elevation does not reduce the inundation time for an individual swell event. In fact, the highest density of swell durations for all PDF values falls around 20 hours. While the duration of a swell event is not dependent on the runup height, The risk of exposing a nest to being flooded multiple times a season can be reduced by moving the nest to a higher elevation, where probability of being overwashed is lower.

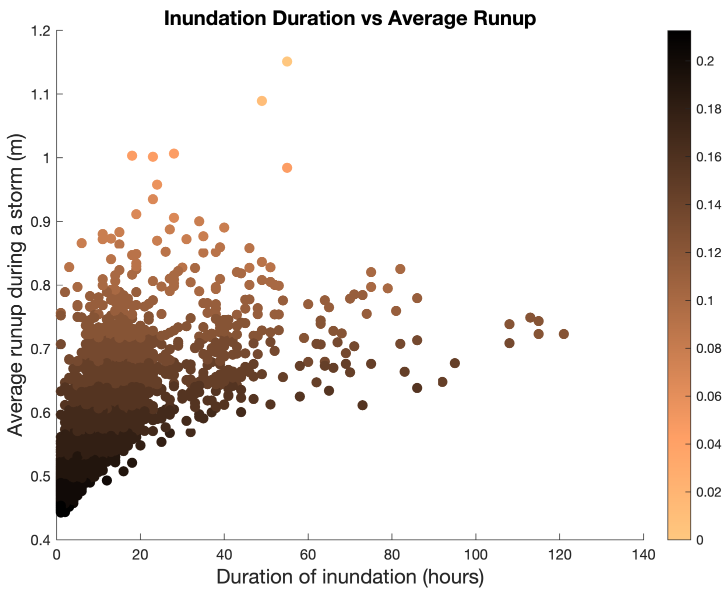


Figure 3.8: The duration of a swell event is plotted against the average runup height during the event for the HyCReWW results. Each point is colored based on the empirical PDF value of the average runup.

The empirical PDF of the durations of all the swell events is shown in figure 3.9, along with the median and inter-quartile range (IQR). The median duration of a swell event was 7 hours and the The lower and upper quartiles were 4 and 11 hours, respectively. This means that any nest that gets overwashed has a significant risk of reducing the viability its eggs.

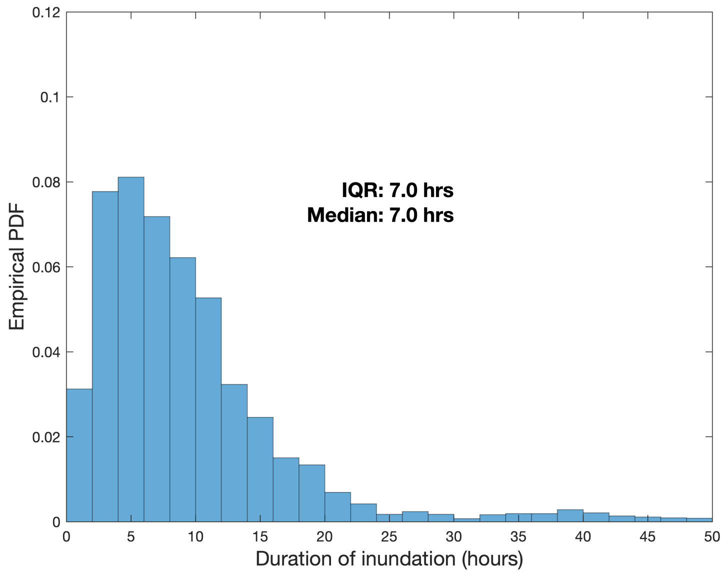


Figure 3.9: Histogram of the empirical PDF of the duration of the swell events modeled with BEWARE 2.0.

3.3.2. Flood durations with BEWARE 2.0 results

The same plots were created for the results of BEWARE 2.0. In BEWARE 2.0, the input conditions were more stringent than those of HyCReWW, and there were only 1088 individual waves modeled during the 40-year model period. This resulted in 148 swell events. The maximum duration plotted in figure 3.10 was 44 hours, which was nearly 80 hours less than the maximum duration of the HyCReWW swell events. This is likely due to the durations of events being cut off because the minimum value of runup modeled was 0.61 m. Interestingly, there were events with a duration of less than 5 hours for higher runup events, which may also be attributed to the high input limitations of BEWARE 2.0. Similarly to HyCReWW, there was a high density of events with low runup and low durations. This can also be explained by the input limitations of BEWARE 2.0. It is clear that there is no correlation of the data, but the small sample size due to the high threshold of 0.61 m of runup makes it difficult to make conclusions based on 3.10.

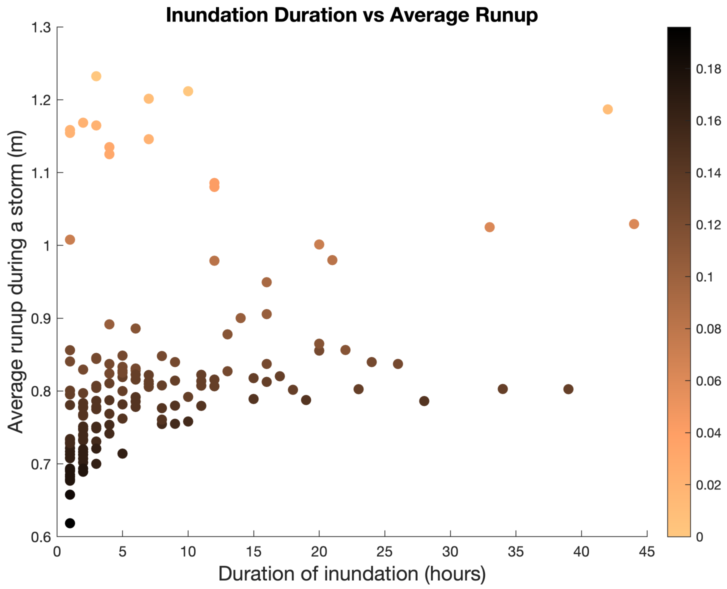


Figure 3.10: The duration of a swell event is plotted against the average runup height during the event for the BEWARE 2.0 results. Each point is colored based on the empirical PDF value of the average runup.

It makes sense based on the analysis of figure 3.10 that the median value of 4 hours of the duration was much lower than the HyCReWW events. The lower quartile was 2 hours and the upper quartile was 10 hours, which is apparent in the skew of the PDF towards the lower durations. In all likelihood, a larger range of wave conditions modeled in BEWARE 2.0 would result in a similar distribution to HyCReWW. Despite the lack of data, the results still show that any runup event is capable of doing significant damage to nests.

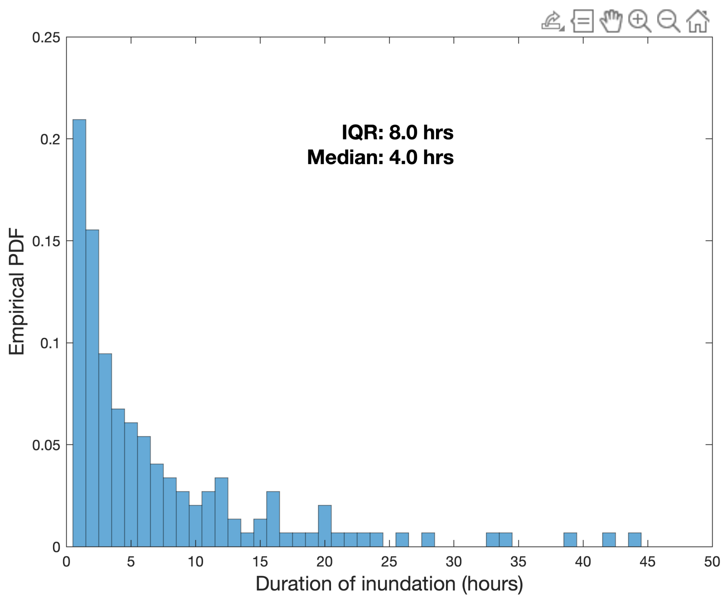


Figure 3.11: Histogram of the empirical PDF of the duration of the swell events modeled with BEWARE 2.0.

3.4. Methodological validation results

In this section, the model performances of BEWARE 2.0 and HyCReWW are compared to each other. The model performances were based on the performance metrics that were the result of each metamodel run for all 6 validation profiles and 10 of the 12 validation conditions, and their comparisons to XBeach for the high and low resolution cases. It should be reiterated that the metamodel performance is not based on the model runs in Ras Baridi, but rather for 6 bathymetry profiles from around the world where an XBeach model has been validated.

The performance metrics calculated for the high (XBeach and the metamodels using high resolution bathymetry) and low resolution (XBeach using high resolution bathymetry and the metamodels using low resolution bathymetry) results of HyCReWW, BEWARE 2.0 and XBeach are plotted in figure 3.12. Comparing the individual metamodels' performances in the low and high resolution columns gives an indication of their ability to produce reliable estimates of runup with low resolution bathymetry, while comparing the two metamodels in each column allows us to rank the models' ability to use low resolution bathymetry.

Comparing BEWARE2.0 metrics in the low and high resolution column, it is apparent that ranges in RMSE are similar, however the median value is lower for the high resolution. The median SI's are similar, but the low column shows a larger range of values than the high resolution case. Both the bias and the RB of the high resolution case are centered around 0, while the bias and RB of the low resolution case skew negative. The median values in general are quite similar between the low resolution and high resolution columns for BEWARE, but the ranges of values are higher for the low resolution results, suggesting a loss of accuracy.

There is a similar story in comparing the HyCReWW metrics to each other. The median RMSEs and SIs are similar, but the range of values in the low resolution case is higher. The RB and bias for the low resolution case, however, performed better than the high resolution case, with median values close to zero. The data ranges for the low resolution case of bias and RB encompassed those of the high resolution case.

In the high resolution column, BEWARE 2.0 had a lower median error and scatter index than HyCReWW, 0.31 m and 0.14, respectively, and had smaller ranges. It's bias and relative bias were strongly centered around 0, also with smaller ranges than HyCReWW. The high resolution profiles of BEWARE 2.0 performed quite well across all metrics. HyCReWW high resolution had an RMSE error of about 0.5 m and a negative bias and relative bias, which in this case indicates an under-prediction of runup. HyCReWW's median scatter index remained low (0.35) with a small range, meaning that that variability of the model results were captured well. The BEWARE 2.0 and HyCReWW data for each of the metrics in the high resolution column did not have much overlap in the data despite having relatively close peaks.

In the low resolution column, the metamodels were run using low resolution bathymetry and the XBeach models were run using high resolution bathymetry. The median RMSEs for each of the metamodels were nearly the same, but HyCReWW had a much larger, evenly distributed spread, while BEWARE's median RMSE was slightly skewed toward the higher values. HyCReWW's median SI was much larger than BEWARE's (0.44 to BEWARE's 0.19), and was skewed towards higher values, BEWARE 2.0 had a median negative bias and RB, that were lower than that of HyCReWW, although HyCReWW had ranges that were larger than BEWARE 2.0.

Generally, BEWARE performed better than HyCReWW in the both the low resolution and high resolution columns for all metrics, with lower spreads and lower median values. Also, the low resolution results had a higher spread but similar averages than the high resolution results for both HyCReWW and BEWARE 2.0.

A closer look at the results of BEWARE 2.0 and HyCReWW reveals no distinct patterns. BEWARE 2.0, for instance, did not perform better based on the reef width. Nor did the models perform better or worse based on the size of the wave conditions. It is possible that the sample size of the profiles and the waves conditions are simply too small to develop any clear correlations in this manner. To explore the performance results for each validation profile in more detail, see Appendix C.

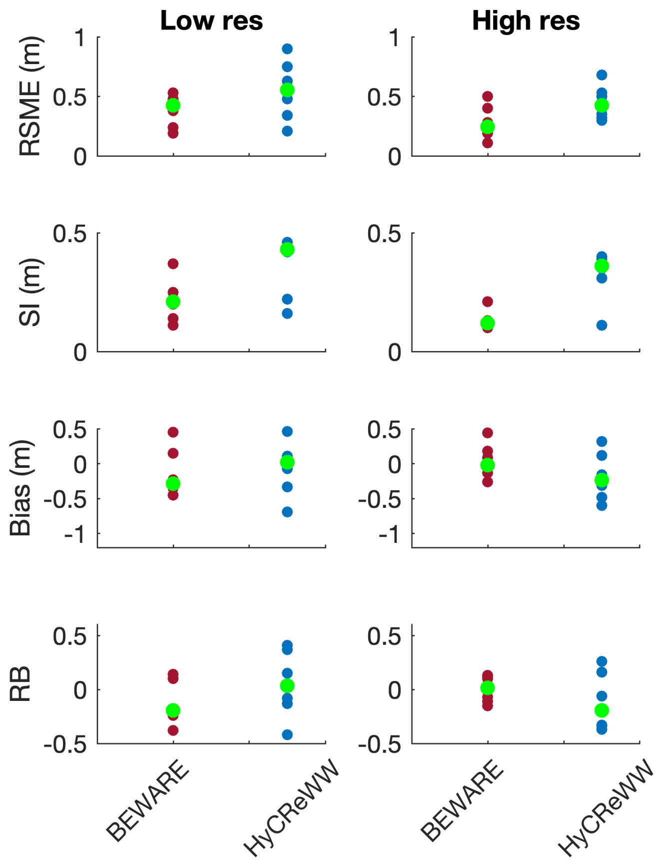


Figure 3.12: Scatter plots for each performance metric are shown for the high and low resolution scenarios. Red points represent BEWARE 2.0 results, blue represent HyCReWW results. The green dots are the medians of the data.The y-axes across individual performance metrics are equal.

The XBeach data in figure 3.13 showed that the median RMSE was 0.55 m, with a spread from 0.2 m to 0.8 m. The median RMSE gives an estimate of how much accuracy is lost when utilizing the low resolution bathymetry profile. The scatter index was 0.25 with a tight, evenly distributed range between 0.2 and 0.4 , with an exception of a high outlier of 0.65. The outlier corresponded to Ningaloo Reef, which underestimated larger runup values, but captured smaller runup values from 0-1 m well. On the whole, XBeach using the low-resolution bathymetry was able reproduce the variability of the high-resolution bathymetry results. The bias and relative bias had median values slightly larger than zero, but had a large ranges from -0.7 m-0.5m and -0.5-0.5 respectively, indicating that the low resolution results both under- and overestimated runup compared to the high resolution bathymetry. These results highlight the extent of the loss in accuracy when using lower resolution bathymetry, and confirm what the results in 3.12 show: the models lose accuracy with decreasing bathymetry resolution.

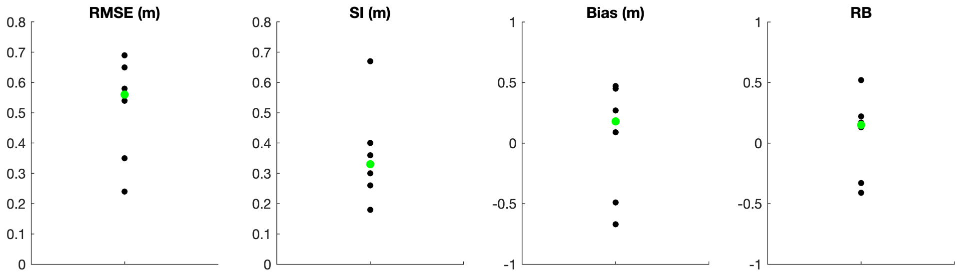


Figure 3.13: Scatter plots for each performance metric are shown for the low resolution scenarios. XBeach high vs low resolution results are also shown in black. Red points represent BEWARE 2.0 results, blue represent HyCReWW results. The green dots are the median values.

4
Discussion

This section discusses the implications of the results for the research question and provides the main sensitivities and potential future applications of this work. First, the likelihood of flooding in Ras Baridi based on HyCReWW and BEWARE 2.0 results is discussed and the results are compared. Second, the methodological validation via the metamodel performance of modeling runup with the validation profiles is discussed and its implications for Ras Baridi are outlined. Lastly, the metamodel uncertainties of both BEWARE 2.0 and HyCReWW are discussed.

4.1. Implications for turtle nesting in Ras Baridi

The median results of running HyCReWW in Ras Baridi with 40 years of hindcast hydrodynamics from 1978-2018 showed a 40-year return periods of about 2 $\pm$0.4 m across all reef widths. It is important for coastal managers to know the spatial variability of wave runup in order to effectively move nests that are at risk of inundation.

Because of the change in beach orientation and reef width, variations of runup along the beach were expected, despite the metamodels' inability to model wave refraction. HyCReWW showed differences of about 0.05 - 0.15 m of runup along the beach for individual return periods. In contrast to HyCReWW, the results of BEWARE 2.0 for all reef widths showed that for the 40-year return period, the variation of vertical runup across the beach was almost 1 m, from 1.8 to 2.7 m from Southwest to Northeast, respectively.

2 meters of vertical runup with a beach slope used in HyCReWW of 0.085 (V:H) corresponds to a horizontal distance of 23.5 m, or 23.65 m up the slope of the beach. The beach width at Ras Baridi varies between 60-70 m wide. The landward extent of the beach is raised frontage road that runs parallel to the water, so it is also important that the nests not be relocated too close to a road where passing cars might pose a threat to hatchlings. The most extreme runup event based on the 40-years of hindcast conditions would put require nests to be moved about 1/3 of the distance of the beach, which is closer to the water than the frontage road. The 1-year return periods across the beach were about 0.9 $\pm$0.15 m, which translates to moving a nest 2.4 m landward.

BEWARE 2.0 uses a default beach slope of 0.1 (V:H), so this means that the model showed 10 m of horizontal variation across the beach (18-27 m). Even for the 1-year return periods, the difference in vertical runup between 50 and 200 m reef width is 0.5 m, or 5-10 m of horizontal variation along the beach. The implies that coastal managers would have to be aware of the variations in reef width in the shore-parallel direction as they work on the beach in order to properly move nests to a safe elevation.

The results in table 3.2 showed that for the 50 m reef width 40-year return period was 0.6 m higher that the same return period for a reef width of 100 m. Using the BEWARE 2.0 results, it may be prudent then, to for managers split the beach into 2 sectors to evaluate nest risk. The Northwest sector which covers the reef until 100 m, and the Southeast sector which covers the beach for reef widths >100 m. The Northwest sector could use the higher runup values associated with reef widths <100 m and the Southeast sector could use the lower runup values associated with reef width values >100 m.

The duration of the modeled runup events is important to deepening the understanding of flood risk to sea turtles as inundation for 6 hours can decreases the viability of eggs by 30% (Pike et al., 2015).

The median durations of inundation found in section 3.3 were 4 and 7 hours for BEWARE 2.0 and HyCReWW, respectively. The incubation period of green turtles is about 50-70 days (Wyneken et al., 2013), so nests should be placed at an elevation where it is unlikely that the nest will be inundated at all during the 2 month period. In that case, the runup elevation associated with a return period of 5 years is a suitable minimum nesting elevation to reduce the risk of inundation. The 5-year return periods along the beach for BEWARE 2.0 and HyCReWW were 1.2-1.3 m and 1.25-1.75 m, respectively.

These results do not include the effects of sea level rise within the 40-year model period, which has been measured to be around 0.08 m. Neither do they include future projections of sea level rise, which have been modeled to range from 0.41-0.77 m by 2100 depending on the emissions scenario (Intergovernmental Panel on Climate Change (IPCC), 2023). With sea levels rising, the wave dissipation function of fringing reefs can be diminished is SLR rates outpace that of the coral growth rates, allowing larger waves to reach the shoreline (Baldock et al., 2014) to damage nesting beaches.

4.1.1. Comparison of metamodel results at Ras Baridi

Figure 4.1 shows the results at Ras Baridi for HyCReWW and BEWARE 2.0 for the 1088 overlapping events. The RMSE is also shown for each of the 4 profiles. The results show that the models captured the variability of the runup in the same way. BEWARE 2.0 generally provided higher larger results of runup for reef widths of 150 and 80 m, whereas HyCReWW's results were slightly larger for reef widths of 170 and 120 m. The profile with a W_r of 80 m had a much larger values for BEWARE 2.0, which was likely due to the fact that this profile had strong matches to profiles with smaller reef flat widths as can be seen in figure 3.5d. This discussion highlights the complexities of assessing wave runup at Ras Baridi and the importance of understanding these variations for effective nest relocation and coastal management decisions.

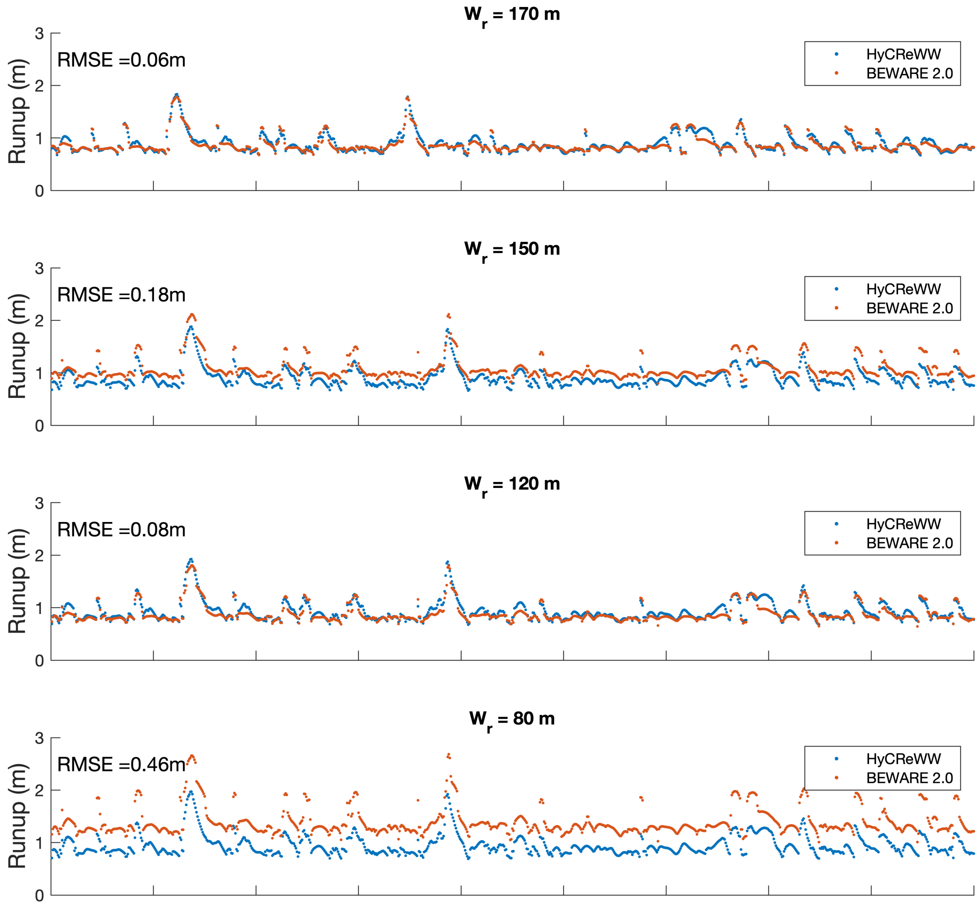


Figure 4.1: Plots comparing HyCReWW and BEWARE 2 results in Ras Baridi for the same 1088 conditions with their RMSE across the 4 profiles.

4.2. Methodological validation

Validation of the metamodels was not possible, as measured runup at Ras Baridi was not available. To overcome this limitation, a comparison of metamodels against validated XBeach models was used to validate the methodology. This comparative approach aimed to instill confidence in the results in Ras Baridi. The performance comparisons enabled a thorough analysis of the performance of how the metamodels performed individually and in comparison to each other in a low data environment.

BEWARE 2.0 using low resolution bathymetry performed well when compared to its high resolution counterpart. The results consistently indicated that the metamodel employing low resolution bathymetry could replicate the variability, albeit with slightly larger errors and increased uncertainty compared to BEWARE 2.0 using high resolution bathymetry. Similarly, HyCReWW, when using low resolution bathymetry, showed strong performance compared to it's high resolution runs, with similar median values, but wider spreads. The effects of the reduced bathymetry resolution and accuracy primarily showed themselves in the wider spread of the data observed in the lower resolution dataset. Importantly, while metamodels exhibited greater variability in the results compared to those using the high resolution bathymetry, the median values of metrics like RMSE, SI and bias all indicated that the overall accuracy remained comparable. Based on the findings, it appears that the results remain useful for estimating runup with meaningful information for coastal managers.

Deploying two metamodels aimed to determine which of the two could be more effectively utilized in a low data environment. In this regard, BEWARE 2.0 outperformed HyCReWW across all metrics for the validation profiles. Bias metrics indicated that BEWARE 2.0 had median negative bias, but the results exhibited a distribution above and below zero, with a wide spread that precluded drawing firm conclusions about performance based solely on the median. These conclusions highlight the strengths of BEWARE 2.0 in modeling runup, its adaptability to different resolution scenarios, and its potential as a tool for predicting runup in coastal areas with varying data resolutions.

4.2.1. Uncertainties in performance results

The data had a larger spread across all metrics than the high resolution data. It is difficult to extract meaningful statistics from such large ranges with only sample sizes of six for each metric. For outliers and biases, without a larger sample size, it is unclear as to whether the distribution of the performance metrics would stay at their present values. The large spread in values could be due, in part to the small sample size.

A possible solution would be to increase the number of validation profiles that are used. This would provide a broader range of scenarios and could potentially be more representative of Ras Baridi. However increasing the number of validation profiles would require the XBeach models to be validated at other locations.

A simpler path to ensure the results are more robust would be increasing the number of hydrodynamic conditions run for the validation profiles. This would increase the confidence in the performance metrics of each profile. With only 10 conditions with a large range of values from 1-5 m waves, it is difficult to measure the performance for each validation profile with certainty. Increasing the number of conditions to fill out the parameter ranges would provide more insight into whether the performance is dependent on the input parameters, and would be easier to discern consistent patterns. It was apparent that for Ras Baridi, the range of values across reef width for both HyCReWW and BEWARE 2.0 grew with increasing return period, implying that larger waves in this models increase the uncertainty of the results. This would be valuable information to assess using the validation profiles and a larger set of input conditions.

4.2.2. Limitations of results

While the metamodel performance for other validated XBeach models helps provide confidence for the application in Ras Baridi, it still does not represent a validation of the metamodels in Ras Baridi. This is part of the challenge of applying models in low data environments. The limited data availability narrows the scope of the usefulness of the results. The data that was available contains it's own assumptions and uncertainties, that propagate uncertainty in the models. This was seen in the sensitivity analysis of HyCReWW for Ras Baridi, where the uncertainty of the coefficient of friction was shown to have an large effect on the wave runup results. Caution is needed when drawing strong conclusions from results of these metamodels in Ras Baridi. The results should be regarded as a first estimate, and a range of values, not as exact values.

It is recommended that the models' performance be further explored and refined by validating the results with real data. Runup data measured in Ras Baridi would validate the results. It would also be of use to measure the bathymetry and topography in detail, that way the validation of the model results can be compared against different resolution data and the sources of uncertainty can be properly diagnosed. The metamodels could also be refined and validated over time in an iterative way, as data in the study region is collected.

4.3. Metamodel Uncertainties

Both BEWARE 2.0 and HyCReWW were designed to be easily applicable and numerically efficient for fringing reef environments where it is notoriously difficult to model hydrodynamics. They employ two different strategies for estimating runup, both of which lead to uncertainties. Those uncertainties are discussed in the following subsections.

4.3.1. Model choice

Both the metamodels are based on data sets derived from XBNH 1-D. For highly variable bathymetry and complex morphological processes, a 2D model that resolves waves and currents in both the cross shore and long shore direction is ideal. Runup can be affected by refracting waves and waves approaching the shore at an angle, trapped long waves, as well as localized bathymetry changes like rhythmic beach patterns.

The dominant hydrodynamics important to reef fronted-beaches like Ras Baridi are often in the cross shore direction. Short waves shoal and break over the reef and the wave energy generally approaches the beach in the shore normal direction. This reduces the longshore currents that could force the beach morphology to change in the longshore direction, or effect wave propagation. However, in the case that the reef profile is highly variable, wave shoaling and breaking may not be uniform along the shore and effect the aforementioned processes.

If waves have a significant directional spread, infragravity waves can be generated and which are an important driver of runup (Reniers et al., 2002). Guza and Feddersen (2012) demonstrated that runup of infragravity waves was dependent on the frequency and directional spread of the incident wave spectrum. Furthermore, long wave shoaling and refraction in the reef flat can cause long waves to become trapped in the longshore direction (Buckley et al., 2022), a process not captured by a 1D model.

Deploying 1D models in Ras Baridi meant that all waves were treated as shore-normal, despite the majority of the waves approaching at extreme angles to the beach. The extraction point of the wave data just inside the bay in deep water was intended to capture the effects of sheltering. However, refraction of waves towards the beach reduces the incoming wave energy by spreading it, and can lead to a reduction in wave heights. The alongshore variability of waves due to refraction and bathymetry variation causes differences in wave setup, which drive horizontal circulation patterns that affect incoming waves. Refraction is not a process modeled in the 1D metamodels used in this report, which means that the incident waves, and thus runup, were overestimated in the metamodels.

2D models require higher resolution inputs to describe the physics involved in wave runup and are much more computationally expensive than 1D models. Without detailed topobathy data and despite the numerous processes that contribute to runup missing from the model, the available data dictated that a 2D model could not be implemented.

4.3.2. Uncertainties implementing HyCReWW

Reef schematizing uncertainties

The first step in applying HyCReWW requires the schematizing of the input bathymetry profile into 4 parameters: fore-reef slope, reef-flat width, coefficient of friction, and beach slope. This process already introduces uncertainty due to the nature of choosing values for the parameters. The reef width was difficult to define for both the low and high resolution bathymetry. It was done using both google earth and the bathymetry profiles themselves. The bathymetry profile from the Allen Coral Atlas had 10 m horizontal resolution so there was a possibility for 10 m of reef width to be left out of the measurement. In the high resolution bathymetry for the validation profiles, the edge location where the elevation began to decrease constantly was used as the seaward extent of the profile. To supplement this, the reef extent was measured using Google Earth's measuring tool. However, seaward extent of the reef was difficult to see, as the reef begins its downward slope and breaking waves in the images obscure the reef. Breaking waves in the images can provide a good indicator of where the reef flat begins, because assuming there steep, uniform fore-reef slope, waves are forced to break near the crest of the reef.

The fore-reef slope was difficult to estimate in general because the slopes of the reef profiles in both the low resolution and the high resolution bathymetry were not constant. For some profiles, the reef depth increased slowly before dropping off. In others, the reef edge was distinct and the drop off into deeper waters was apparent. It was assumed that the slope started at the previously defined seaward end of the reef flat and extended to the seaward end of the profile. This may not be the best way to define the slope however, as ostensibly the fore-reef slope parameter is important for modeling the processes wave shoaling and breaking. Any differences between the slopes in the reef profile are missed by this method.

Data on the beach slopes was missing for both the validation profiles and the Ras Baridi profiles. For Ras Baridi, the availability of sediment samples from the beach provided enough information to use an empirical relationship between grain size and beach slope. However there have been many equations presented relating grain size and beach slope. The one used is simply a fit to sediment data compiled from other studies of grain size and beach slope, with its own inherent error. Indeed, for a beach slope of 0.85, the upper and lower 95% confidence bands fall at around 0.12 and and 0.05, respectively (Bujan et al., 2019). This covers over half of the input limitation that HyCReWW can handle. For Ras

Baridi, this may not have been an issue as runup on the beach was low, and the relative importance of the beach slope in determining runup is likely smaller that other processes like wave breaking and energy dissipation due to friction. This was certainly the case in the sensitivity analysis.

In future studies, it would be prudent to analyze the importance of beach slope for higher runup values to provide more confidence to the sensitivity of this parameter. Regarding the validation profiles, there was no information regarding beach slope, and no sediment data to rely on. There were much larger hydrodynamic conditions used of 3 and 5 m, so it is assumed that the importance and sensitivity of the beach slope in the model was higher.

The coefficient of friction is not a parameter that is readily defined for coral reefs. There is not a set method for determining a reef's coefficient of friction (Lindhart et al., 2021; Pearson et al., 2017; Pequignet et al., 2011), in fact it is generally a parameter that is found by model calibration. However for Ras Baridi it proved important, displaying a wide range of values for runup for the same input condition. There may not be a way to reduce the uncertainty around the value coefficient of friction without using a highly calibrated model with detailed and local data. The relative importance of c_f in the wave runup processes could merely be a function of the low range of wave heights in Ras Baridi, and could decrease in sensitivity in areas with higher waves. This would also be an area of exploration in a future study.

SA and input screening

The sensitivity analysis was used as a way to understand the importance of the uncertainty of the HyCReWW metamodel inputs, and to screen the input parameters to save computational time when running the model. The results of the SA showed that the reef width, the beach slope, the MSL proxy, and the reef slope had little importance for their range of values.

There may be a couple reasons why these parameters may have little effect on the outputs. For the beach slope, it is the fact that for smaller run up values, beach slope does little to dissipate run up in comparison to other processes like wave breaking and shoaling. For the MSL proxy, its most likely that the small range of values considered are not significant when added to the larger water level changes. The reef slope ranges considered are all quite steep in comparison to the wave lengths of the incident waves, and so there is not much change in wave breaking occurring. The range of reef widths are quite small compared to the metamodel limitations (0-1500 m reef width), so the changes in output with respect to the other parameters whose ranges fill a large percentage of the model limitations (WL,H_s, c_f) is quite small. It is most likely this fact that puts c_f in the 2^{nd} rank for importance, is that it fills the complete range of the model limitations, with an order of magnitude difference between its minimum and maximum values.

4.3.3. BEWARE profile matching uncertainties and input limitations

The first step of implementing BEWARE 2.0 is the matching of the input profile to a profile in the BEWARE database. As discussed in chapter 2, this happens in two steps. First the input profile is matched against a set of RCPs, which are grouped by their similar morphology and hydrodynamics. Each group is represented by one profile, for which the runup is extracted. This is repeated for the 7 highest matches, and a weighted ensemble of runup is calculated.

However, the second round of matching, where the profile representing the group is used to extract runup, introduces a potential source of error. The profiles that represent each group of RCPs may not always align perfectly with the input profile, leading to notable variations in runup. For instance, this discrepancy became apparent when matching profiles in Ras Baridi, particularly for profile 4 with a reef width of 50 meters. In this case, the matching process resulted in a significant increase in runup compared to other reef widths.

Improving the matching process within BEWARE 2.0 could reduce it's vulnerability of matching the wrong profile to an input profile. Despite this vulnerability, BEWARE 2.0 performed better in this study than HyCReWW. This suggests that, although the profile matching process may imperfect, it appears to be a more reliable modeling method than the schematizing of the input profile. It's important to note that BEWARE 2.0 faced challenges when handling variations in beach slope and coefficient of friction. As a result, the model's sensitivity to these parameters remains unknown.

5

Conclusions and Recommendations

The primary aim of this study was to provide reliable estimates of sea turtle nest flooding as a function of beach elevation in Ras Baridi, Saudi Arabia. The research sought to provide information that could assist coastal managers in designating safe nesting elevations for sea turtles and enable informed decisions on nest relocation. Ras Baridi is a low data environment, so methods of providing reliable flood estimates were explored so that the findings could be useful in other low data environments.

This was achieved by using two different metamodels, BEWARE 2.0 and HyCReWW, to estimate runup with 40 years of wave and water level hindcast data. BEWARE 2.0 and HyCReWW employ different methods of modeling: HyCReWW uses fully schematized bathymetry, while BEWARE 2.0 uses actual bathymetry. The sensitivity of HyCReWW to the uncertainty of the input parameters was explored using Borgonovo's method. It was found that that for the mild wave climate of Ras Baridi HyCReWW was sensitive to changes in the coefficient of friction. To capture the alongshore variation of the reef width, runup was modeled for 4 different profiles along the beach. The likelihood of runup induced flooding along the beach for both metamodels was expressed in return periods from 1 to 40 years for each profile.

Sea turtle egg viability can be reduced by 30% when they are inundated for 6 hours (Pike et al., 2015), so the duration of modeled runup events was also explored. It was found that the median durations of inundation for any flood event were 4 and 7 hours for BEWARE 2.0 and HyCReWW, respectively. For this reason, any inundation event during the 2 month incubation period presents a high risk for nests. A 5-year return period runup level as a minimum nesting elevation was presented as a suitable low risk option for nest relocation. The 5-year return periods along the beach at Ras Baridi were 1.25-1.75 m and 1.2-1.3 m for BEWARE 2.0 and HyCReWW, respectively.

The study outlined the challenges of determining key parameters at Ras Baridi, such as fore-reef slope, reef-flat width, coefficient of friction, and beach slope, and their implications for model accuracy. It also discussed the uncertainties associated with these parameters and the need for further investigations.

Without locally measured waves and water levels, the results in Ras Baridi were not able to be validated. A methodological validation was instead used to provide confidence that the methods were appropriate and reliable so that they may be used in other flood risk assessments of fringing reef coastlines. The metamodels were compared to validated XBeach models to contextualize their performance with low resolution bathymetry.

While both metamodels demonstrated satisfactory performance in comparison to high-resolution bathymetry results, BEWARE 2.0 showed better performance metrics. It appears that relying on a real bathymetry profile, even if it is low resolution, fares better than schematizing the reef. Thus, it is recommended that the results of BEWARE 2.0 in Ras Baridi should be used over the results of HyCReWW. BEWARE 2.0 is also recommended over HyCReWW for use in other low data environments.

However, it's important to acknowledge that the study's sample size was limited, leading to wide ranges in the performance metrics. To improve confidence in the results, future studies should consider increasing the number of validation profiles and exploring a wider range of hydrodynamic conditions. It is also recommended that future studies consider that the current estimates of the return periods may change as the sea level in the Red Sea rises.

The findings of this study hold broader implications beyond marine turtle nesting sites. The methodology and insights gained here can be extrapolated to benefit various other beach-nesting species which are vulnerable to coastal flooding. By adapting and applying the metamodels like BEWARE 2.0 to different locations, critical flood risk assessments can be made. This can aid in the strategic planning and conservation efforts for a diverse range of coastal wildlife that rely on undisturbed nesting sites. The adaptation of such models for other species could pave the way for a comprehensive understanding of flood risks in diverse coastal ecosystems.

The methodology developed in this study addresses a fundamental challenge: making reliable flood risk assessments in data-scarce environments. This is particularly significant for rapid assessments of flood potential during large-scale evaluations, especially concerning protected areas and critical infrastructure zones. The ability to gauge flood risks using metamodels in such contexts can significantly enhance disaster preparedness and response strategies. It offers a preliminary insight into potential flood hazards, enabling authorities to make informed decisions promptly. This approach could play a pivotal role in proactive risk management, safeguarding both natural habitats and human settlements along vulnerable coastlines. Further research and application of these methodologies can substantially contribute to resilience building in the face of escalating climate uncertainties.

In conclusion, BEWARE 2.0 offers a valuable tool for estimating runup in coastal areas with varying data resolutions. The modeling of runup in Ras Baridi with BEWARE 2.0 yielded results that can assist coastal managers in their protection of sea turtle nests from flooding. However, further validation and refinement are necessary, with an emphasis on collecting real-world runup data in Ras Baridi and examining the sensitivity of model results to key parameters. These findings contribute to the understanding of coastal flood risk modeling and its application in low-data environments, ultimately aiding in the protection of sea turtle nesting sites and other vulnerable coastal regions.

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A

Site description of Ras Baridi

This section includes the physical description of the Red Sea and sea level rise trends in the Red Sea.

A.1. Site description

The Red Sea is incredibly warm and saline due to the limited exchange and input of freshwater. Depending on the location and the season, the temperature and salinity range from 21 to 29° C and 3.6% to 4.1%, respectively. For reference, the North Sea temperature and salinity range from 5 to 20° C and 3 to 3.5%, respectively. The north Red Sea is dominated by prevailing north-westerly winds with averages from 7-12 km/hr, with some variation seasonally and regionally due to the topography. The winds predominantly blow along the long Northwest-Southeast axis of the sea.

The Red Sea is unique in the fact that no rivers flow into it, so sediment is supplied via other modes of transport. There are *wadis* or seasonal streams that flow during extreme rainfall that transport silt and fine quartz sand. Aeolian sediment transport due to strong winds provide a significant supply of fine silt to quartz. Coarse grained material from sand to gravel is consists of large quantities of carbonate material (Mancini et al., 2015) that originates from the corals.

A.1.1. SLR in the Red Sea

The Intergovernmental Panel on Climate Change (IPCC) has constructed global carbon emissions scenarios based on social and environmental changes called shared socioeconomic pathways (SSP). SSP 2.6 is a scenario where the global mean stays below 2.0°C warming relative to 1850-1900 (median) with implied net zero emissions in the second half of the century. SSP 8.5 is an extreme scenario in which no further climate policy is enacted. Under SSP 2.6 and 8.5 the median projections for sea level rise (SLR) in 2100 in the Red Sea are 0.41 m and 0.77, respectively. This rise will influence the hydrodynamics in different ways in the Red Sea, but for the purposes of this study, the effect on run up and coastal flooding is of particular interest. Future flooding scenarios will inform mitigation measures for local communities and sea turtle nesting beaches. They also provide an opportunity for the local ecology to be incorporated into the solutions, such as sea grass beds as wave dissipation devices, or coral reefs as submerged breakwaters.

B

Marine turtle nesting habits

A vulnerable part of life for sea turtles is nesting. Female sea turtles nest multiple times during the months-long nesting season. They bury their eggs on sandy beaches, laying clutches of hundreds of eggs in the process (Pike et al., 2015; Ferreira et al., 2021; Shimada et al., 2021a). The first stages of life for all marine turtle species have very high mortality rates (Mancini et al., 2015). Eggs have average incubation times of 60 days, so threats to nests like poachers or animals are common. Incubation requires very specific conditions for temperature, salinity, and moisture, with slight changes affecting the survival of an egg. The temperature of the clutch plays a large role in determining the sex of the turtle. Moisture and salinity effect the oxygen exchange across the shell. Increased temperatures or seasonal changes to temperature have the potential to change the male to female ratio of marine turtle hatchlings, which has long term effects on the population Wyneken et al. (2013). Coastal inundation for short or long periods of time can change the temperatures, reduce oxygen exchange and increase salinity, which can severely reduce emergence rates of clutches (Pike et al., 2015). Hatchlings also face threats from animals, coastal developments and light pollution. Coastal developments can reduce the available nesting space and may force nesting females to nest in closer to the waterline, putting clutches at higher risk to inundation or washing clutches away. Hatchlings also rely on moonlight to navigate to the water, and light pollution of nearby buildings can confuse them, leading to dehydration and exhaustion, as well as exposing them to the dangers of the human built environment.

Many species of sea turtles return every 3-6 years to the same coastal regions to nest for two to six months of the year (Hawkes et al., 2009; Wyneken et al., 2013; Lohmann and Lohmann, 2019). They lay multiple clutches of eggs during the nesting season and spend the time in between nesting events foraging in waters surrounding the nesting beaches (Ferreira et al., 2021; Shimada et al., 2021a). The processes surrounding the marine turtle's selection of nesting beaches is not well understood. It is thought that beach slope, sediment characteristics, hydrodynamics, surrounding ecology and natal homing are all thought to play a role (Wyneken et al., 2013; Lohmann and Lohmann, 2019; Ware et al., 2021; Horrocks and McA Scott, 1991). As there is no post natal care for hatchling sea turtles, the selection of an appropriate nesting beach is crucial to the their survival. The sea turtles that nest in the Red Sea are the Green and Hawksbill turtles (Shimada et al., 2021a,b; Mancini et al., 2015; Scott et al., 2022). While the totality of the nesting habits are not known in the many islands and remote beaches of the Red Sea, there have been recent efforts to document and track the temporal and spatial distribution of the nesting species.

The highest density of Green turtle nesting that has been studied occurs along the beaches of Ras Baridi, where they have been studied since the late 1980's (Shimada et al., 2021a,b; Mancini et al., 2015). The nesting season in Ras Baridi for this species historically lasts from July to November with a peak in September/October, but recent studies have shown a a temporal shift with a nesting season starting in April and peaking in August (Mancini et al., 2015; Shimada et al., 2021a,b). According to a recent multiyear study where nesting females were tracked during the nesting season, approximately 5.9 clutches were laid per season.

The time between consecutive nesting events or re-nesting time was between 9-20 days. During the re-nesting time, the females foraged within a large area surrounding the nesting beaches, to which they were very likely to nest at again (Shimada et al., 2021b). Green turtles are known to forage on seagrass beds and likely forage on the expansive seagrass beds surrounding Ras Baridi (Mancini et al., 2015).

Hawksbill turtles nest throughout the Red Sea, with a very small amount nesting in Ras Baridi sporadically. From the recent multiyear study, the Hawksbill turtles in Ras Baridi nest from April to July with a peak in May. The average clutch number per female studied was 2.74, but as the study started late in the nesting season, the actual number of clutches could be as much as double what was recorded (Shimada et al., 2021a). Internesting times and foraging grounds for the Hawksbill turtles that nest in Ras Baridi are unknown but it is believed that the fringing reefs in the surrounding area are preferred as they mainly feed on corals and sponges (Mancini et al., 2015).

C

Metamodel performance results

This section contains a further analysis of the metamodel results for the validation profiles. Metamodel results of the individual profiles for both HyCReWW, XBeach and BEWARE 2.0 can be found in this section.

C.1. XBeach low resolution performance

The results of comparing XBeach using the 12 input conditions for the high and low resolution profiles are shown in figures C.1 and C.2. The average results in figure C.1 show an RMSE of 0.53 m and a SI of 0.31 m. The bias metrics are low simply because the scatter is evenly distributed to either half of the 1:1 line. The individual profiles show strong positive and negative relative biases with the exception of Molokai and Funafuti. Funafuti, Ipan Reef, Mokuleia and Ningaloo all have RMSE's larger than 0.5 m and biases larger than 0.4 m

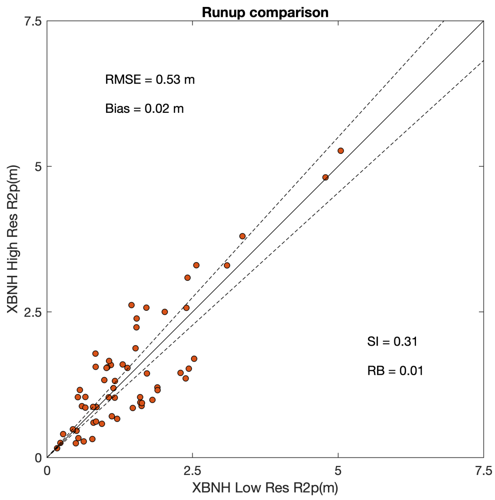


Figure C.1: The results of XBeach using high resolution bathymetry (y-axis) against the results of XBeach using low resolution bathymetry(x-axis) for the same 12 input conditions. The dashed black lines in the figure correspond to the 10% upper and lower deviation from 1:1 line.

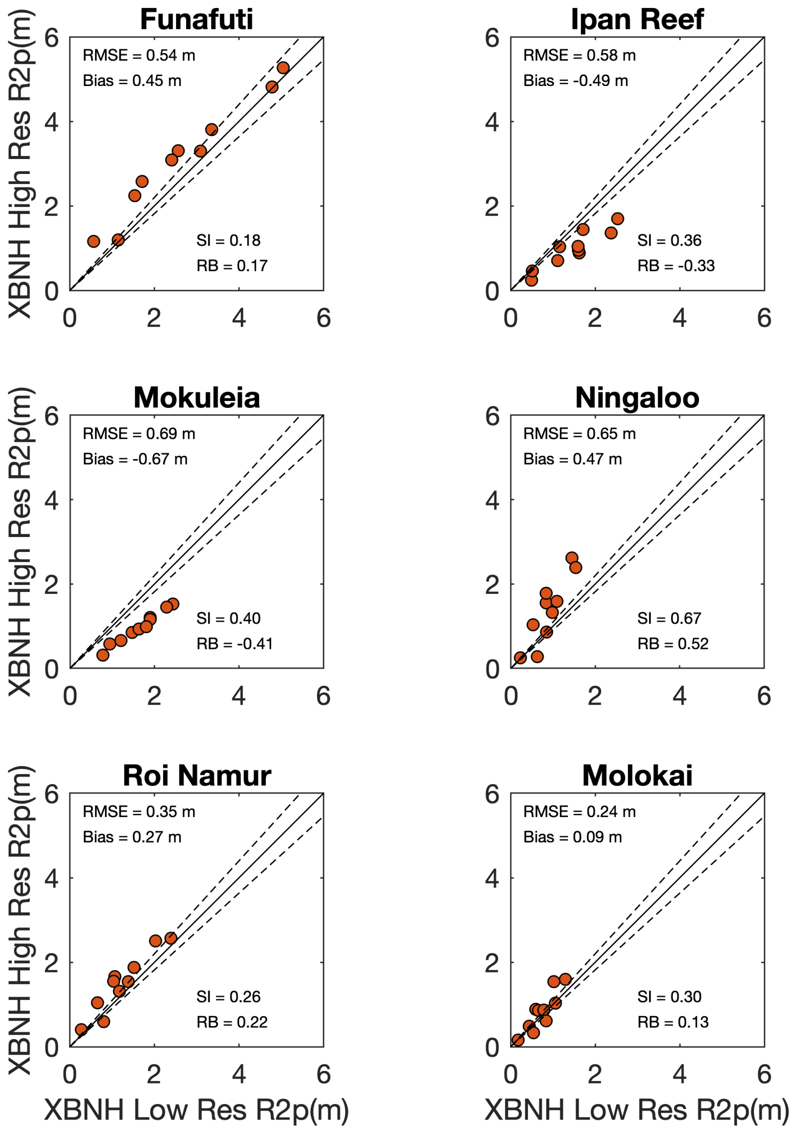


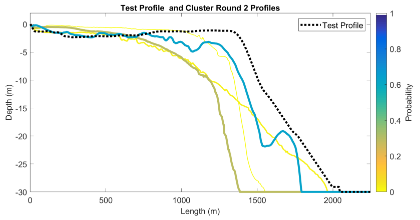
Figure C.2: The results of XBeach using high resolution bathymetry (y-axis) against the results of XBeach using low resolution bathymetry(x-axis) for the same 12 input conditions. The dashed black lines in the figure correspond to the 10% upper and lower deviation from 1:1 line.

C.2. BEWARE performance

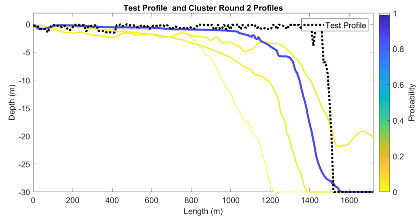
The results of BEWARE 2.0 for the 12 wave conditions in 2.5 were calculated for high resolution bathymetry and low resolution bathymetry for each of the 6 validation reef profiles. The results of the input profile matching are presented for the low resolution and high resolution bathymetry. Then the runup results are compared against the XBeach baseline results for the same conditions using high resolution bathymetry.

Profile matching

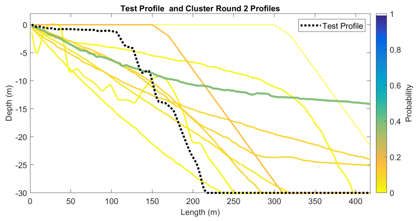
The high and low resolution bathymetry for Ningaloo, Funafuti, Molokai, Ipan Reef, Mokuleia, Roi Namur were used as input for BEWARE 2.0. The model first matches the input profiles to profiles in its database in two rounds: the first round is based on morphology, and the second is based on morphology and hydrodynamic similarity. The results of the second round are shown below. In some instances, the high and low resolution profiles had a high probability match with a similar profile, such as Ipan Reef and Roi Namur. The other locations' high and low resolution profiles differed in their higher probability matches.



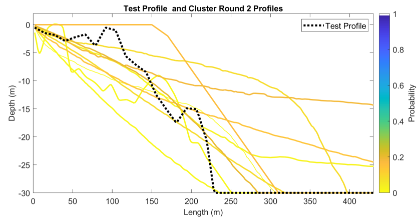
(a) Ningaloo high resolution



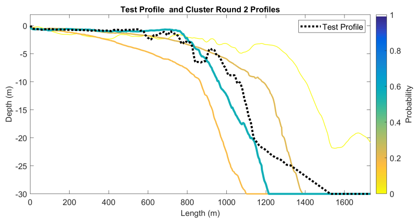
(b) Ningaloo low resolution



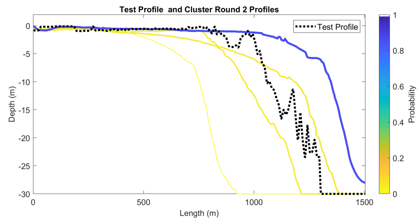
(c) Funafuti high resolution



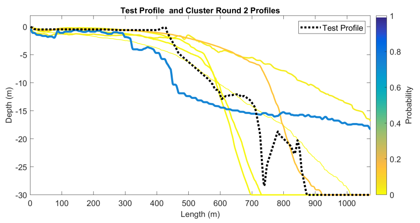
(d) Funafuti low resolution



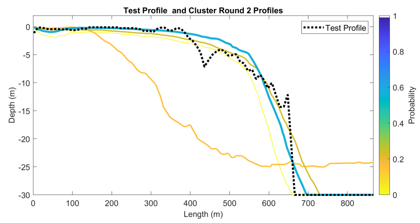
(e) Molokai high resolution



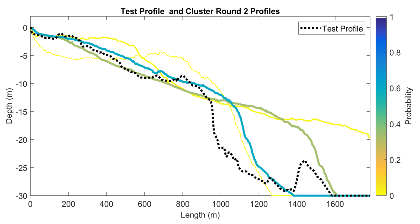
(f) Molokai low resolution



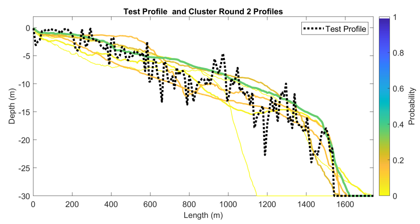
(g) Ipan Reef high resolution



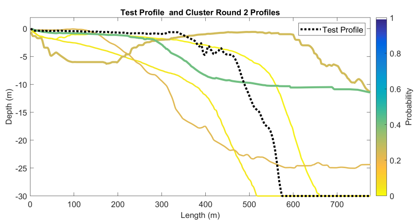
(h) Ipan Reef low resolution



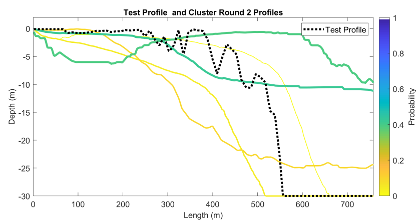
(i) Mokuleia high resolution



(j) Mokuleia low resolution



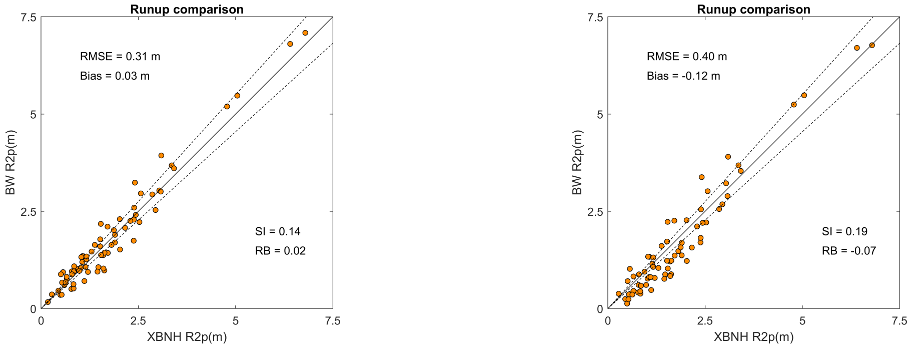
(k) Roi Namur high resolution



(l) Roi Namur low resolution

Figure C.3: The results of the second round of profile matching in BEWARE 2.0 for each of the high (left column) and low resolution (right column) bathymetry profiles.

The results of XBeach and BEWARE 2.0 for the 12 hydrodynamic conditions were plotted for the high and low resolution bathymetry. The SI, RMSE, bias and RB were calculated for each profile in figures C.5 and C.6 and then for all profiles combined in figures C.4a and C.4b.



(a) All profiles high resolution

(b) All profiles low resolution

Figure C.4: The results of BEWARE 2.0 for each of the high (left) and low resolution (right) bathymetry profiles. The dashed black lines in the figure correspond to the 10% upper and lower deviation from 1:1 line.

The BEWARE 2.0 results were compared against XBeach results for each of the high resolution profiles, shown in figure C.5. The results show for each profile a strong alignment with XBeach results. The different maximum runup values correspond neatly with decreasing reef width.

The results of the low resolution profiles (BEWARE using low resolution bathymetry and XBeach using high resolution bathymetry) are shown in figure C.6. The profiles with the larger reef widths (Mokuleia, Molokai, Ningaloo, and Ipan Reef) slightly underestimated runup, shown by their negative bias. Funafuti and Roi Namur overestimated runup, shown by their positive biases.

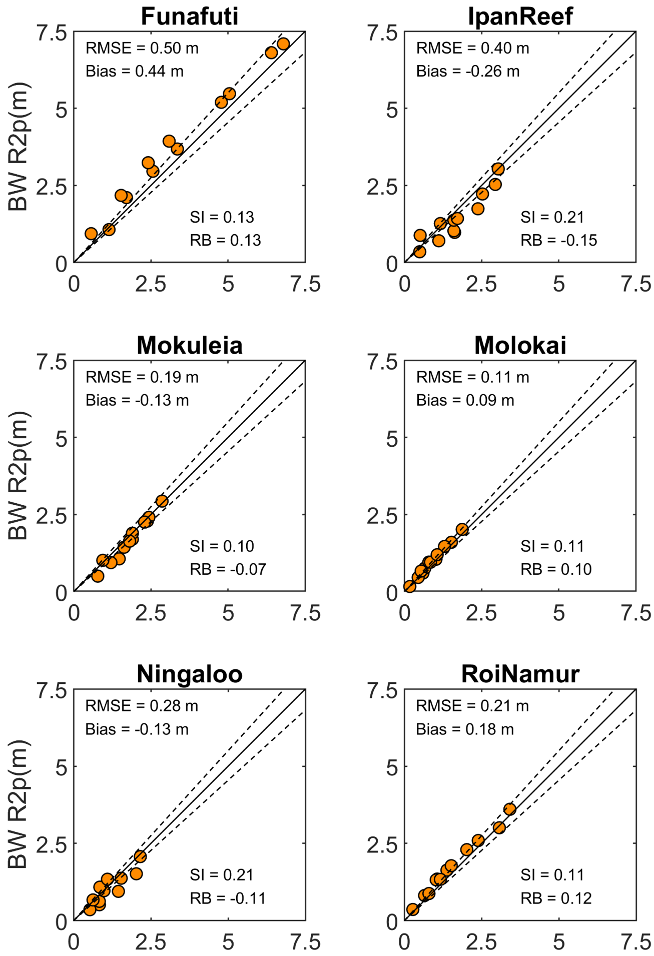


Figure C.5: The results of BEWARE 2.0 (y-axis) for each of the high resolution bathymetry profiles against the results of XBeach (x-axis) for the same 12 input conditions. The dashed black lines in the figure correspond to the 10% upper and lower deviation from 1:1 line.

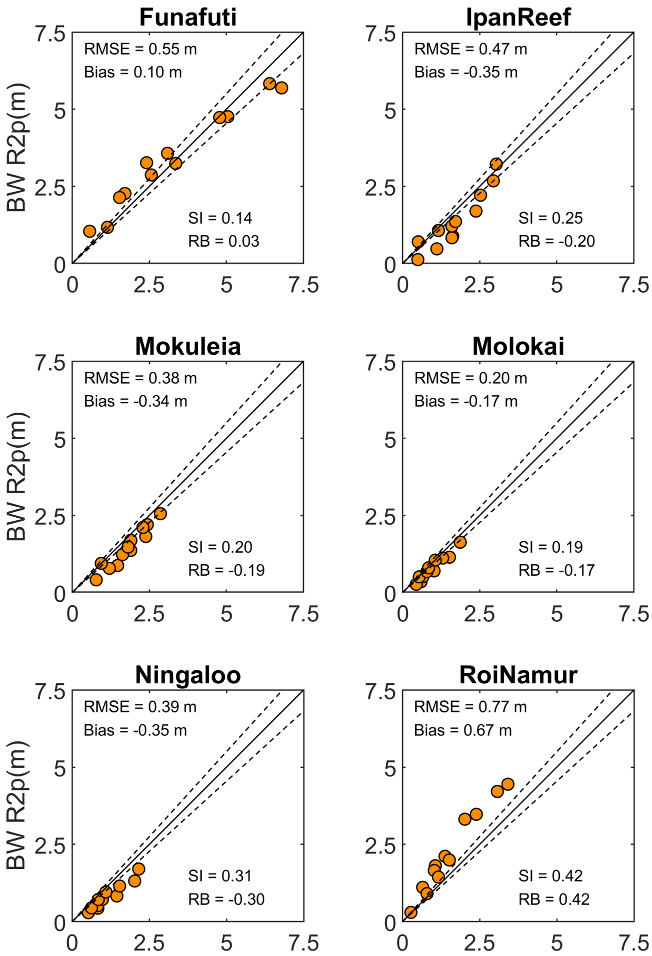


Figure C.6: The results of BEWARE 2.0 (y-axis) for each of the low resolution bathymetry profiles against the results of XBeach (x-axis) for the same 12 input conditions. The dashed black lines in the figure correspond to the 10% upper and lower deviation from 1:1 line.

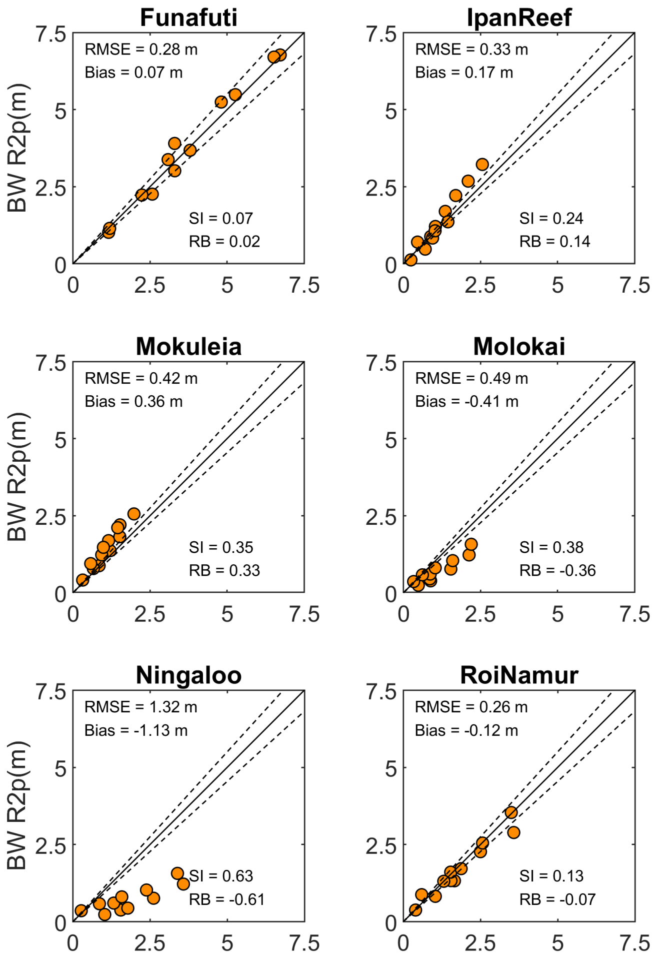
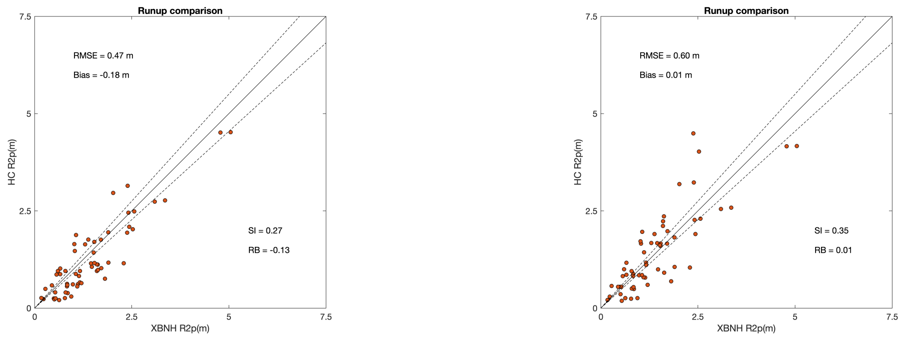


Figure C.7: The results of BEWARE 2.0 (y-axis) for each of the low resolution bathymetry profiles against the results of XBeach (x-axis) for the same 12 input conditions. The dashed black lines in the figure correspond to the 10% upper and lower deviation from 1:1 line.

C.3. HyCReWW performance

The results of XBeach and HyCReWW for 10 hydrodynamic conditions were plotted for the high and low resolution bathymetry. The SI, RMSE, bias and RB were calculated for each profile in figures C.9 and C.10, and then for all profiles combined in figures C.8a and C.8b.



(a) All profiles high resolution

(b) All profiles hybrid resolution

Figure C.8: The results of HyCReWW (y-axis) plotted against XBeach (x-axis) for all of the validation profiles and the same 10 input conditions. The high resolution (a) and low resolution results (b) are shown. The dashed black lines in the figure correspond to the 10% upper and lower deviation from 1:1 line.

The HyCReWW results were compared against XBeach results for each of the high resolution profiles, shown in figure C.9. For the Ningaloo, Mokuleia and Ipan Reef profiles, there was significant negative bias and underestimation of runup. For Roi Namur and Molokai there were slight positive biases implying overestimation of runup.

The low resolution case (HyCReWW results using low resolution bathymetry vs. XBeach using high resolution bathymetry) are shown in figure C.10. There is no discernible pattern amongst the plots, other than the large errors they all share.

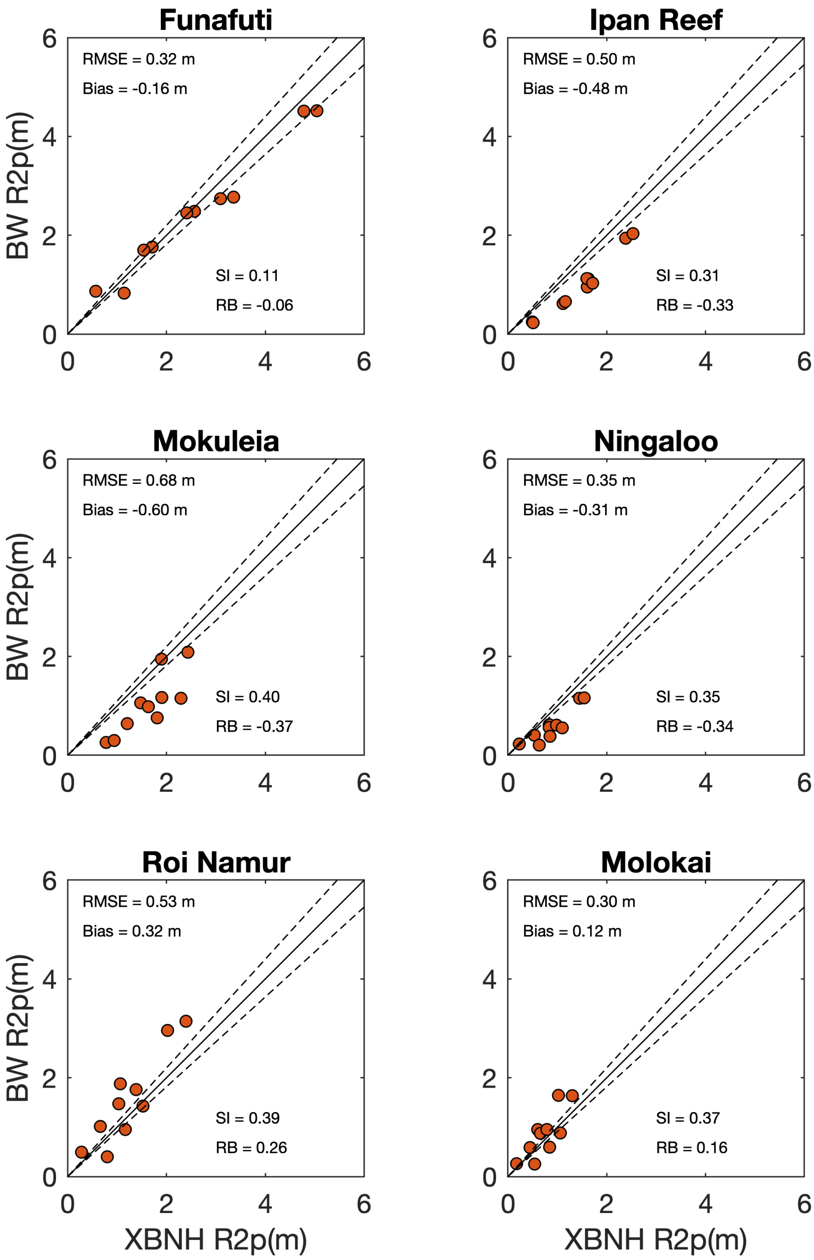


Figure C.9: The results of HyCReWW for each of the high resolution bathymetry profiles against the results of XBeach for the same 12 input conditions. The dashed black lines in the figure correspond to the 10% upper and lower deviation from 1:1 line.

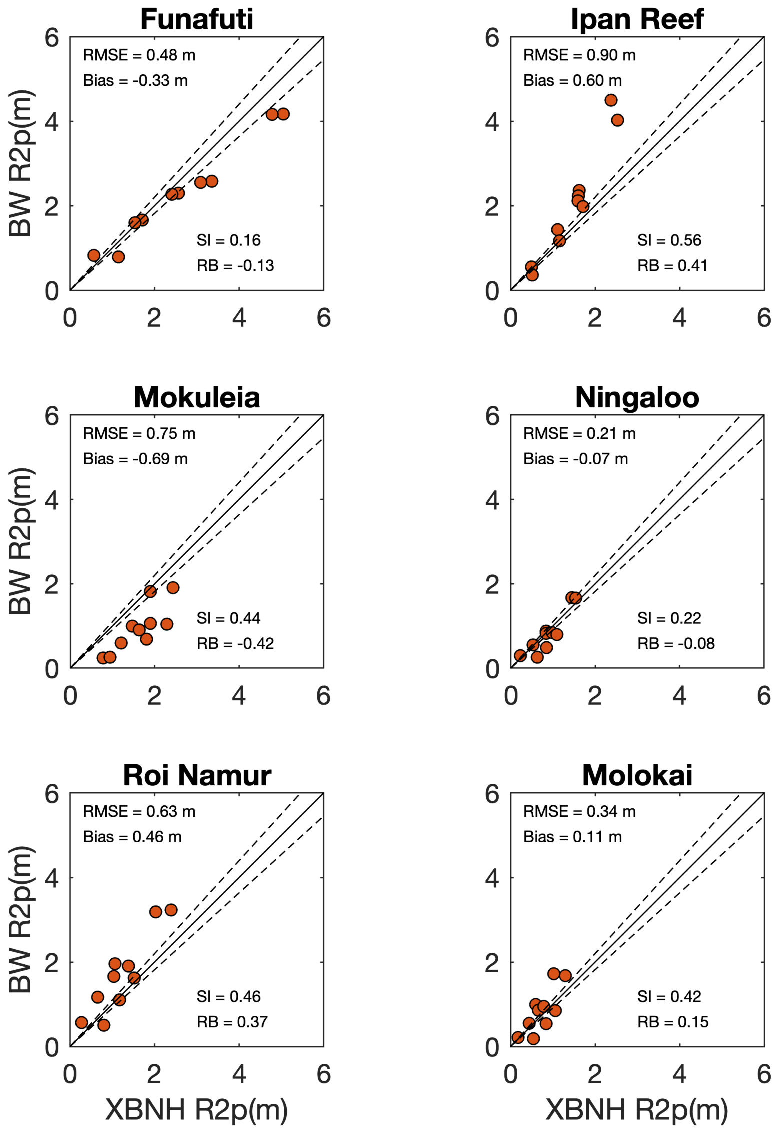


Figure C.10: The results of HyCReWW for each of the low resolution bathymetry profiles against the results of XBeach for the same 12 input conditions.The dashed black lines in the figure correspond to the 10% upper and lower deviation from 1:1 line.