European Research Area for Climate Services

ECLISEA

European advances on CLImate Services for Coasts and SEAs

REVIEW OF METHODOLOGIES

FOR REGIONAL STUDIES OF SEA SURFACE DYNAMICS

Work Package 2 - Deliverable 2.B

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Summary

Many offshore and coastal applications such as impact assessment, risk management, characterization of energy resources require long-term homogeneous information about sea surface dynamics. Different downscaling approaches have been developed to provide databases with these requirements. They can be categorized in three approaches: a) dynamical downcaling; b) statistical downcaling and c) hybrid downscaling. The strategies applied in each downscaling category differ regarding the historical forcings, the numerical or statistical model and its configuration used. Different advantages or drawbacks can be identified in each approach. In this report, we review the three downscaling approaches describing different methodologies within each category to generate historical data of sea surface dynamics for regional studies. Differences between the approaches are discussed with the purpose of obtaining a high-quality estimation of the total water level for coastal flooding assessment.

1. Introduction

Coastal zones have always attracted humans because of their rich resources, particularly their supply of subsistence resources; for logistical reasons, as they offer access points to marine trade and transport; for recreational or cultural activities; or simply because of their special sense of place at the interface between land and sea. The development and utilization of coastal zones has greatly increased during the recent decades and coasts are undergoing tremendous socio-economic and environmental changes—a trend which is expected to continue in future (Neuman et al., 2015). Besides people and economic activity concentrate in coastal areas, also vital environmental assets like saltmarshes, mangroves and coral reefs that underpin multiple ecosystem services are contained (Nicholls et al., 2018).

Anthropogenic factors enhance the natural characteristic of the coast to be exposed to changes due to climate variations (e.g. sedimentation-erosion processes), and consequently to be affected by climate impacts (e.g. coastline regression, damages of maritime works, inundation, impoverishment of marine ecosystems, etc). In addition, the adjacent seas to coasts play an important role on activities from different sectors, such as maritime trade, offshore energy or shipping.

At European context, there is an increasing demand of regional information of sea surface dynamics at different time scales (seasonal, long-term, climate change) by a wide variety of stakeholders with a policy and a business purpose (e.g. coastal risk management, assessment of offshore renewable energies, navigation related companies, etc). The basic climate information is related with the present climate covering several decades in other to analyze the climate variability and have the best representation as possible of extreme events (the more years of data, the best capture of extreme and interannual variability). This information is essential to understand the main drivers responsible of the observed climate impacts on the coast.

The current development of the climate model systems and ocean models do not consider the simulation of wave dynamics. Wave data is available from buoys, voluntary observing ships, satellite altimetry, and numerical models forced by wind from climate models (Stopa et al., 2013). Buoys provide ground truth for validation of observational and model data. Despite the lack of spatial coverage, missing data and time series not sufficiently long, buoy data provides a critical source of information for assessment of climate variability (e.g., Bromirski et al., 2005; Menendez et al., 2008). Ship visual observations were shown by Gulev and Grigorieva (2006) as an accurate source of information, but have limited coverage in the Southern Hemisphere and in extreme conditions (Gulev et al., 2003). Altimetry data from satellites provide significant wave height sea-state parameter for more than 20 years. Numerous studies have used satellite altimetry to describe the wind and wave climate as well as extreme events (e.g., Young, 1999; Woolf et al., 2002; Hemer et al., 2010a; Young et al., 2011; Izaguirre et al., 2011). However, satellite data are not available on the coastal and high latitude regions and altimeter products do not provide spectral and wave period information. An alternative for obtaining long-term and mostly homogeneous descriptions of wave climate is using numerically generated wave hindcasts. Numerical simulations using third generation

phase-averaged wave models such as WAve Model (WAM) described by Wamdig (1988) and WAVEWATCH III (WW3) of Tolman et al. (2002) have greatly complemented observational data in terms of resolution and coverage improving the knowledge in wave climate as well as providing information of smaller scale processes.

Empirical data supports the idea that waves at the sea surface account for more than half of the energy carried by all waves on the ocean surface, the contribution of tides, tsunamis, coastal surges, etc. (Kinsman, 1965). There are two types of wind waves at the ocean surface. During the generation and growing processes, they are designated as wind sea. As waves propagate away from their generation area, or when their phase speed overcomes the overlaying wind speed, they are called swell. Swell waves are known to travel long distances across the globe (Barber and Ursell 1948; Munk et al. 1963). For example, swells generated in extratropical areas of the southern oceans spread energy throughout the entire global ocean, and are a potentially important component of the wave climate in most ocean basins in both hemispheres (Alves et al., 2006). Wind seas are generated locally and are strongly coupled to the local wind field; swells are generated remotely and are not directly coupled to the local wind field (Semedo et al., 2011). Wind-waves generated by intense storms become ocean swells as they leave their generation zone, traveling long distances across the globe (Alves et al., 2006). Therefore, coastal waves present the special feature that they are the integrated result of the dynamics of the ocean surface over a large region of influence. For example, in the case of Europe, Figure 1 illustrates the oceanic surface where waves can be generated and propagated towards the North Sea (top) and the south Atlantic (bottom) coasts in Europe. Therefore, wave modelling presents the special characteristic that global wave simulations should be performed to adequately characterize waves at coastal locations.

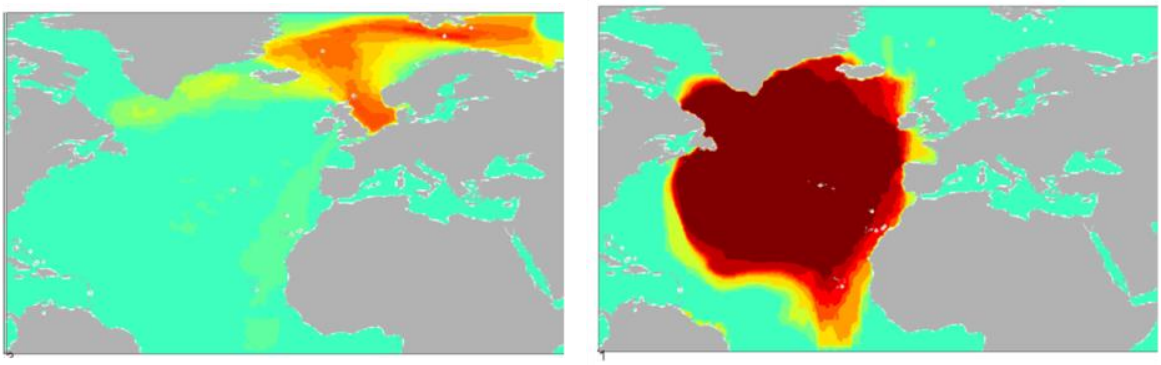


FIGURE 1 AREA OF GENERATION AND PROPAGATION OF WAVES THAT CAN REACH THE COAST IN THE NORTH SEA (LEFT PANEL) AND SOUTH ATLANTIC EUROPEAN COAST (RIGHT PANEL).

Long-term wave databases from numerical models have allowed to improve the knowledge of deep water wave climate of deep water or large-scale wave climate with the advantage of not presenting the problems of instrumental buoys such as missing data, time series not sufficiently long or sparse locations. However, the spatial data resolution is not

usually enough for coastal applications, and wave transformation processes nearshore are not accounted for.

Downscaling is the process of increasing the spatial resolution of the climate information. In the case of sea surface dynamics, it involves also the simulation of physical process and meteorological variables not considered in global climate model. After reviewing the main determinants in the generation data of sea surface dynamics, three aspects determine the downscaling approach to obtain regional wave information:

1) The current development of the climate model systems and ocean models do not consider the simulation of sea surface dynamics.
2) Swell waves are known to travel long distances across the globe.
3) The assessment of local coastal impacts requires sea surface conditions at high spatial and temporal resolution taking into account the regional heterogeneities.

Downscaling methodologies to generate sea surface dynamics at regional scale can be categorized in three approaches: a) dynamical downscaling based only on numerical simulations; b) statistical downscaling that uses mathematical techniques; c) hybrid downscaling which combines wave modelling and statistical techniques. The dynamical approach consists of nesting higher resolution models that are able to model wave generation and transformation processes (see Figure 2). The statistical downscaling is based on empirical models that link meteorological or sea surface variables at coarser resolution to local variables. Hybrid methodologies, which combines numerical simulations (dynamical downscaling) with mathematical techniques (statistical downscaling), have been developed mainly to generate wave information at high spatial resolution nearshore. Therefore, they are usually applied to downscale wave regional conditions. Dynamical and statistical downscaling approaches use wind data or wave data at coarse resolution to obtain waves at higher resolution. Different methodologies within each approach have been proposed depending of input data.

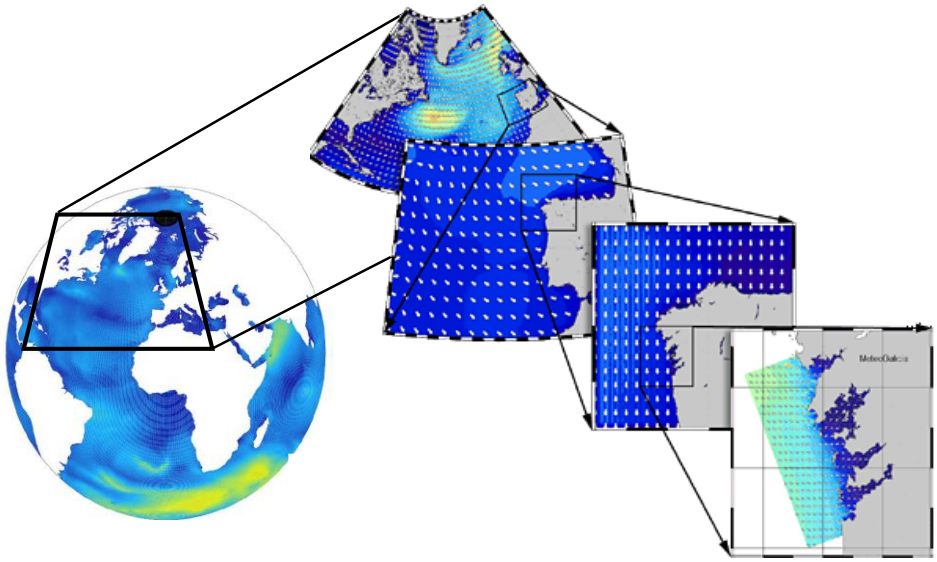


FIGURE 2 DYNAMICAL DOWNSCALING APPROACH.

2. Downscaling approaches

2.1 Dynamical downscaling

The general methodology to generate waves or storm surge differs mainly due to the spatial scale of the physical generation processes. For this reason, we separate the description of the dynamical modelling strategies of each sea surface dynamic.

2.1.1 Wave databases

The dynamical downscaling increases the spatial resolution of global models by means of nesting regional model in the area of interest. Because waves are not outputs of the global climate models and wind waves are composed of wind seas and swells which can spread energy throughout the entire global ocean in some areas of the world, waves should be generated at global scale forced by wind fields using a wave generation model. Regarding the dynamical process to transfer wave climate from deep water to shallow water, a wave propagation model at local scale is nested to the wave boundary conditions from the wave generation model, simulating the wave transformation processes due its interaction with the bathymetry.

Figure 3 synthetizes the different strategies applied to generate waves at regional and local scale. The baseline input data to simulate waves using a wave model (e.g., third generation phase-averaged wave model) are wind fields from an atmospheric reanalysis. Global wave hindcasts are forced by global winds with a spatial resolution ranging from 0.25° to 2.0°, depending on the dataset used. Regional wave hindcasts can be obtained nesting a regional model to global wave conditions and forcing the model using global wind fields or downscaled regional wind fields (e.g, using a mesoscale numerical weather prediction model). In semi-enclosed seas or fetch-limited wind wave generation areas, regional wave simulations do not need to be nested to global wave conditions but it is very convenient to be forced by reginal wind fields. Nearshore wave hindcasts with a spatial resolution around kilometers are usually generated using wave models with high-resolution bathymetric which resolves shallow water wave transformations. The wave boundary conditions can be defined from a global wave hindcast with higher resolution along the coast or a regional wave hindcast.

Several examples of the different strategies to developed wave databases at global, regional and nearshore scale are described below.

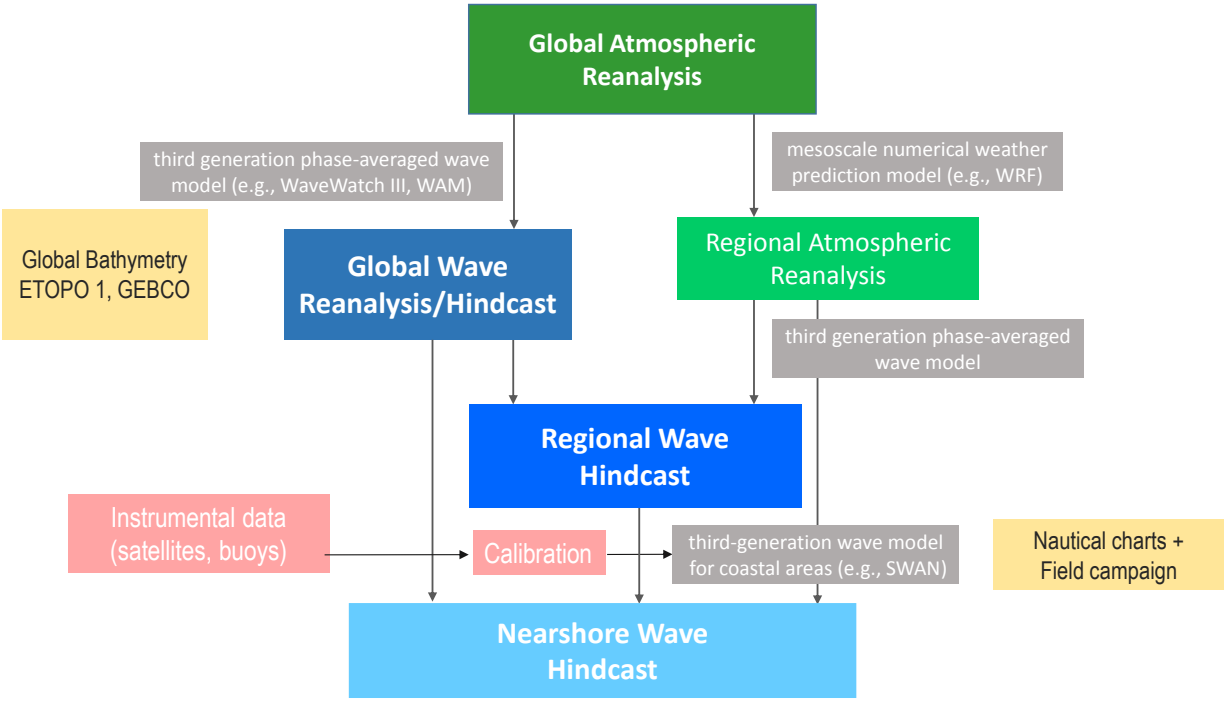


FIGURE 3 METHODOLOGY SCHEME TO GENERATE WAVE HINDCASTS AT DIFFERENT SPATIAL RESOLUTION

GLOBAL WAVE HINDCAST

The quality of the wave data from numerical models depends on the wind forcing and resolution. Reanalysis datasets, which are based on the best available models and data assimilation techniques, are most suitable for production of wave datasets (Stopa et al., 2013). There are a variety of these products, with different resolution, assimilated data, and historical period covered.

The National Centers for Environmental Predictions (NCEP) produced the global Reanalysis I and II (R1 and R2) datasets covering respectively from 1948 and 1979 to the present time at 1.9 resolution every 6 h (Kalnay et al., 1996; Kistler et al., 2001). Swail and Cox (2000) and Graham and Diaz (2001) used R1 to force a spectral wave model covering the globe and the Pacific Ocean. Reguero et al. (2012) developed Global Ocean Wave (GOW) database at 1.5°×1° resolution from 1948 to present based on R1 and R2. The European Centre for Medium-Range Weather Forecasts (ECMWF) created ERA-40 1957–2001 at 1.125 available every 6 h (Ster et al., 1998; Uppala et al., 2005). ERA-40 is a coupled atmosphere-wave model utilizing WAM to produce wave heights, periods, and directions at 1.5 resolution. Newly available reanalysis datasets, such as NCEP's Climate Forecast System Reanalysis (CFSR) for 1979–2009 at 0.34° available every hour and ECMWF's ERA-Interim for 1979-present at 0.7° available every 3 h, have updated physics and improved assimilated data (Saha et al., 2010; Dee et al., 2011). The CFSR and ERA-Interim datasets perform superior to earlier reanalysis datasets developed by NCEP and ECMWF.

NCEP has utilized the CFSR surface winds to create a hindcast wave dataset at 0.5° resolution using WW3 v3.14 for the period 1979–2009 (Chawla et al. 2013). Rascle and

Ardhuin (2013) developed two 0.5° global wave hindcasts; one from 1994 to 2012 based on CFSR and the other from 2005 to 2012 forced by ERA-INTERIM. GOW2 is generated by Pérez et al. (2017) using the version 4.18 of WW3 with a two-way nesting multiple grids run simultaneously and using CFSR winds and ice coverage. This database improves resolution in coastal areas and near the poles, compared with previously developed wave hindcasts. The effect of tropical cyclones is also well-captured thanks to the high resolution of the forcings and the wave model setup. Besides providing more than 37 years of hourly sea state parameters (e.g. significant wave height, peak period, mean wave direction), series of 3-h spectra at more than 40000 locations in coastal areas are also available which provide a valuable information to define wave boundary conditions in regional simulations.

As an example of the dynamical process followed to generate waves at global scale, Figure 4 shows the global parent grid (0.5°×0.5°), the two regional grids covering the Arctic and Antarctic areas (0.25° latitude×0.5° longitude) and the grid covering continental coastal areas and ocean islands globally (0.25°×0.25°) used in the generation of GOW2 database. The polar grids are defined to increase efficiency by confining the smaller time steps required near the poles. The coastal grid is defined to improve the representation of ocean islands and coastal features. It is designed to include all grid-points at depths below 200 m and the surrounding area within 1.5 degrees.

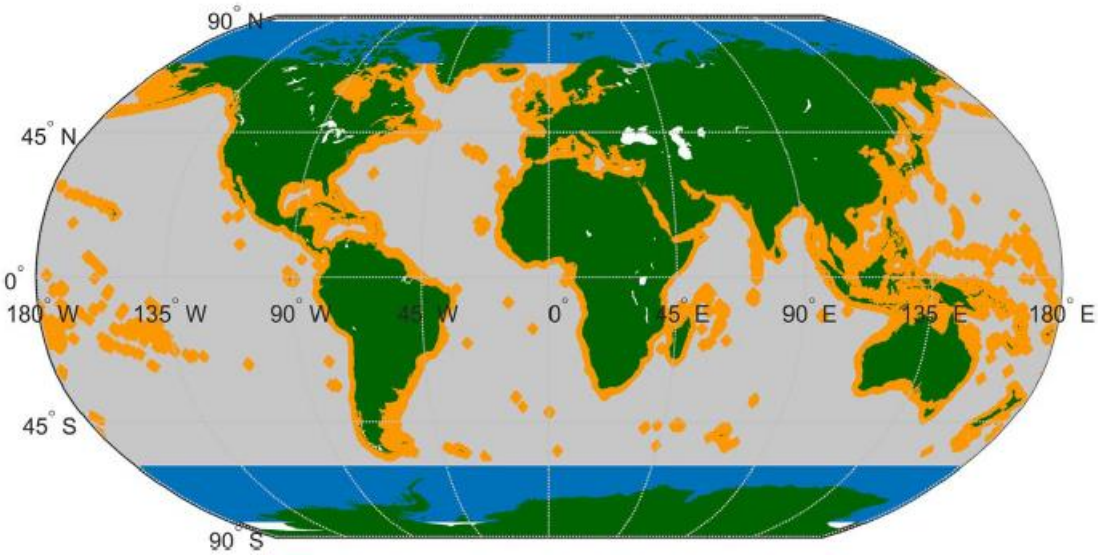


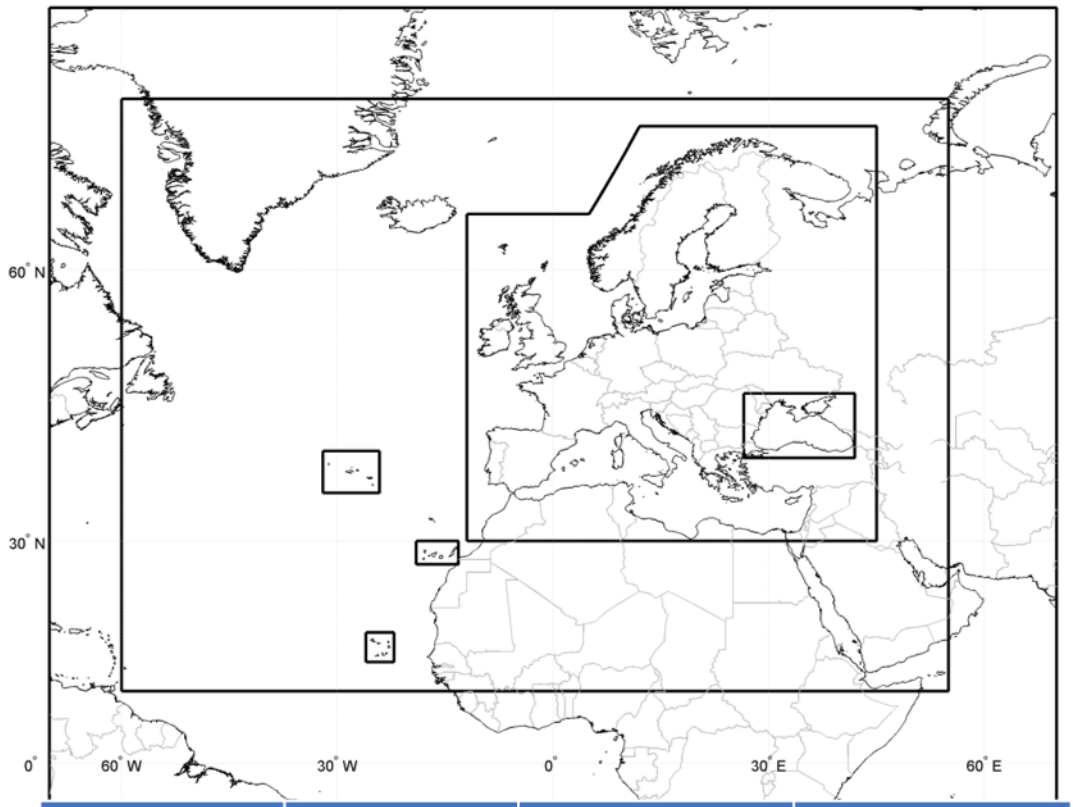
FIGURE 4 MODEL DOMAINS. GLOBAL (0.5°×0.5°) IN LIGHT GRAY, ARCTIC AND ANTARCTIC (0.25° LATITUDE×0.5° LONGITUDE) IN BLUE, AND COASTAL (0.25°×0.25°) IN ORANGE

REGIONAL WAVE HINDCAST

Many wave hindcasts have been developed in different ocean areas. For example, for the North Sea, the Norwegian Sea and the Barents Sea (Reistad et al., 2011), on the Central and South Pacific (Durrant et al., 2013), the waters surrounding New Zealand, which include part of the Tasman Sea and parts of the Southern and southwestern Pacific Oceans (Gorman et al., 2013), in the Indian Ocean (Kumar et al., 2018), in the Gulf of Mexico (Appendini et al., 2014).

In this review, two regional hindcasts are described in detail as an example of two different procedures to generate waves in the North East Atlantic European coast. The first case started simulating waves at a global scale and nesting grids with increasing resolution and forcing all the grids using a global wind fields at a resolution around 0.25°. The second example shows a regional hindcast in the North East Atlantic Ocean starting with a regional computational grid covering the whole North Atlantic Ocean forced by a regional wind reanalysis. A wave hindcast in the Mediterranean Sea is described as an example of a semi-enclosed sea.

A wave hindcast at high spatial resolution, named GOW-Europe, was created to provide a homogeneous historical reconstruction of wave conditions along the whole coast of the EU region (i.e. Atlantic coast, Mediterranean Sea, North Sea, Baltic Sea and Black Sea) (Menéndez et al. 2015). GOW-Europe is designed from a multigrid approach based on the overlapping of two-way nested domains. Figure 5 specifies the spatial domains and resolution of the nesting grids used to generate waves along the European coast at 15 km. The generation and propagation of the sea surface waves of GOW-Europe are simulated with the model WAVEWATCH III v4.18. The ice coverage and wind fields come from CFSR reanalysis (Saha et al., 2010). This database presents high skill to reproduce historical extreme wave events when time series of significant wave heights are compared with buoy records due to the high resolution of wind fields and the high spatial resolution of the wave model computational grid.



Domain	[Latmin Latmax]	[Lonmin Lonmax]	[Δlon Δlat]
Global	[-80.0, 80.0]	[0.0, 360.0]	[1.5, 1.0]
North Atlantic	[10.0, 74.0]	[-60.0, 55.0]	[0.5, 0.5]
Europe	[30.0, 72.0]	[12.0, 45.0]	[0.125, 0.125]
Azores	[36.0, 41.0]	[-32.0, -24.125]	[0.125, 0.125]
Canarias	[27.0, 30.0]	[-19.0, -13.125]	[0.125, 0.125]
CaboVerde	[14.0, 18.0]	[-26.0, -22.0]	[0.125, 0.125]
Black Sea	[36.0, 41.0]	[32.0, 24.125]	[0.0625, 0.0625]

FIGURE 5 SPATIAL DOMAINS OF GOW-EUROPE

The 44-year (from 1958 to 2001) HIPOCAS wave hindcast for the North East Atlantic European coast (Pilar et al., 2008) was generated using a fine grid in the North East Atlantic coastal areas of Europe. The wind fields were obtained by a local area model that was applied in the areas adjacent to the European coasts, which was forced by the results of the NCEP reanalysis. The wind fields produced by the local area model have a spatial resolution of 0.5° and a time step of 1 h. A version of the WAM model that allowed two-way nesting was adopted and calculations were made with nested grids allowing a fine resolution in the coastal areas of Europe (see Figure 6).

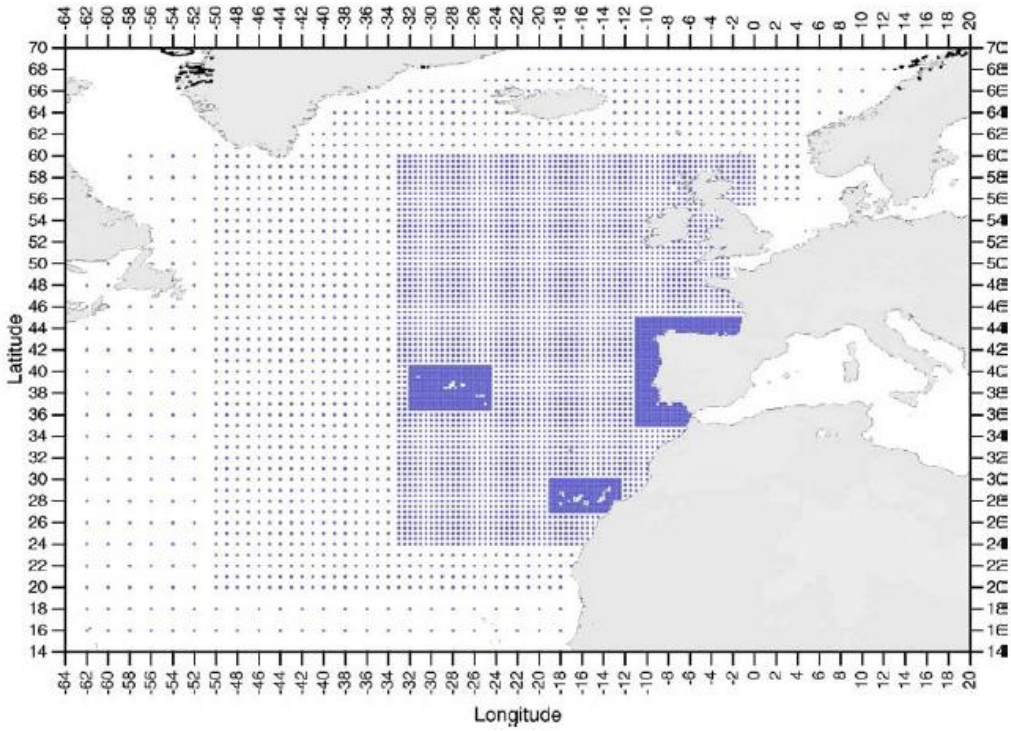


FIGURE 6 BATHYMETRY GRID DEFINITION FOR 6 NESTED GRIDS OF HIPOCAST DATABASE.

Wave hindcast in the Mediterranean Sea has been implemented on a time window covering 36 years (1979- 2014) (Mentaschi et al., 2015). The wave model is forced by the 10-m wind fields obtained by means of the non-hydrostatic model WRF-ARW (Weather Research and Forecasting – Advanced Research WRF) version 3.3.1 (Skamarock et al., 2008). A Lambert conformal grid covering the whole Mediterranean Sea with a resolution of about 0.1 degree in longitude and latitude has been used. Initial and boundary conditions for atmospheric simulations were provided from the CFSR (Climate Forecast System Reanalysis) database (Saha et al., 2010). Generation and propagation of sea waves have been modeled using WavewatchIII®, version 3.14 (Tolman, 2009). A 336x180 regular grid covers the whole Mediterranean Sea with a resolution of 0.1273×0.09 degrees, corresponding to about 10km at the latitude of 45◦N (see Figure 7).

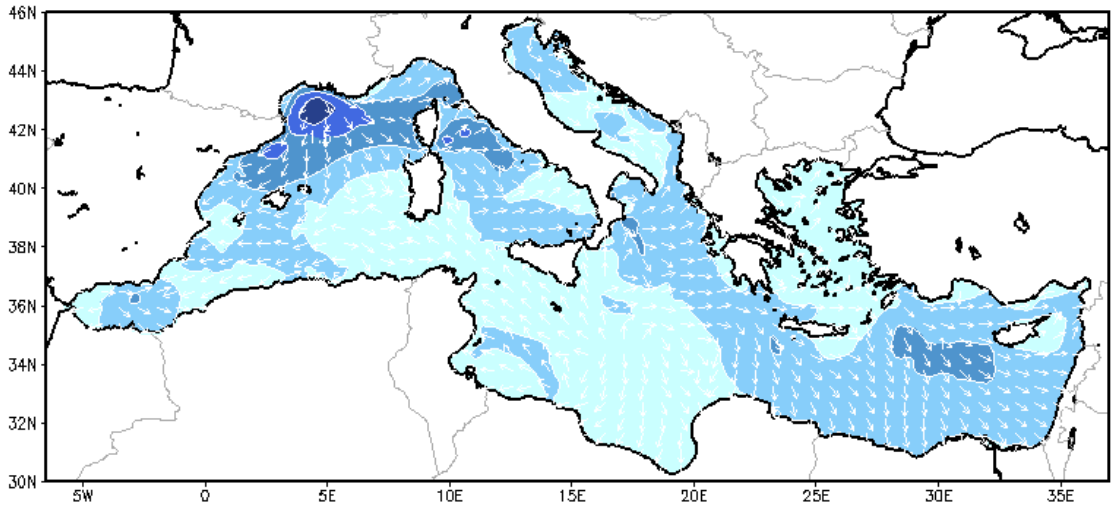


FIGURE 7 WAVE SIMULATION DOMAIN FOR THE HINDCAST IN THE MEDITERRANEAN SEA.

NEARSHORE WAVE HINDCAST

The huge number of studies which include the development of a historical nearshore wave database does not allow to reference all of them. In this report, only two examples are described due to the different approach followed to generate the high-resolution wave databases.

The work developed in Rusu et al. (2008) extends the wave HIPOCAS simulations to shallow water where the bottom effects start being important for the wave predictions. The followed strategy was to use the results of the WAM runs performed in HIPOCAS to be used as boundary conditions for a shallow water model (SWAN model). SWAN is a third-generation wave model, developed at Delft University of Technology, that computes random, short-crested wind-generated waves in coastal regions and inland waters and accounts for physics related with shallow waters. Figure 8 shows the spatial domains to obtain wave conditions along the west Iberian coast.

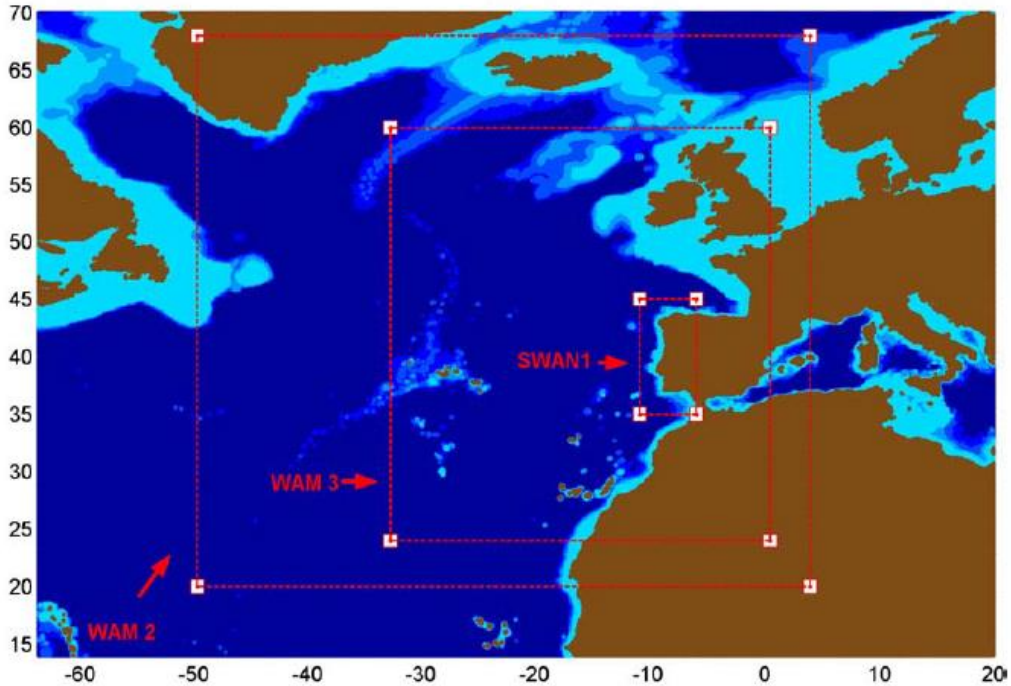


FIGURE 8 SPATIAL DOMAINS OF THE WAM AND SWAN SIMULATIONS IN RUSU ET AL. (2008)

The historical database of waves along the coast of Cuba (Regional Wave Reanalysis, ROW) was generated to have spatially and temporally homogeneous hourly wave data available for a period of more than 30 years (1979-2017) at a spatial resolution of about 1.0 km to provide a robust characterization of the maritime climate for different coastal engineering applications within the project "Evaluation of impacts and vulnerability in the North Western coastal zona of Cuba" developed by IHCantabria for the Economic Commission for Latin America and the Caribbean (ECLAC). The distinctive feature of this wave database is the wave boundary conditions which are defined by spectral data from GOW2 wave hindcast at 0.25° resolution and the previous calibration of the wave conditions using satellite data. Wave propagation to the coast using the SWAN model (Simulating Waves Nearshore, Booij, 1999), using bathymetry obtained by digitizing nautical charts, assimilation of field campaigns and global bathymetry data sources and using an unstructured computational grid (Naciones Unidas, 2018). The annual mean significant wave height is represented in Figure 9 to show the spatial domain of numerical simulations.

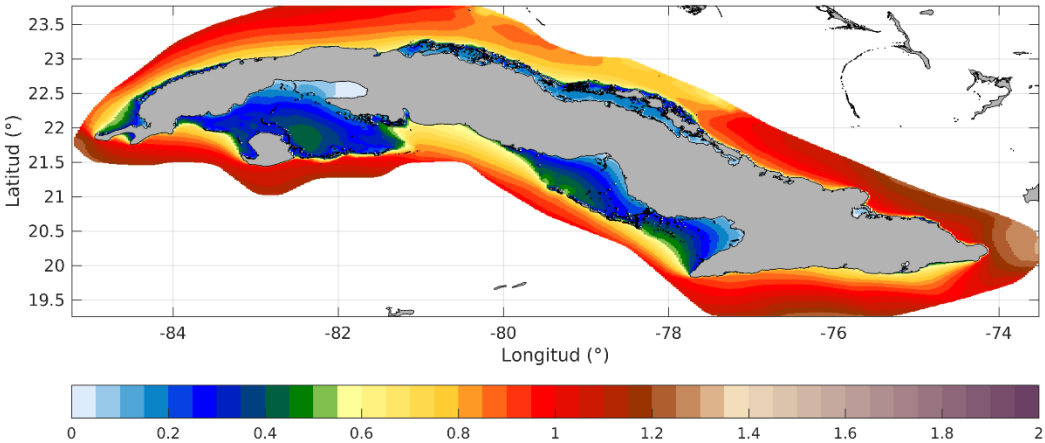


FIGURE 9 SPATIAL NUMERICAL DOMAIN OF THE REGIONAL WAVE REANALYSIS ALONG THE COAST OF CUBA.

2.1.2 Storm surge databases

In the case of storm surge, long-term databases from numerical models are simulated differently to wave databases. Regional modelling does not require to be nested to global simulations because this sea surface dynamic is generated by regional and local physical processes. Figure 10 summaries the different strategies applied to generate storm surge at spatial scale along the coast adequate for regional studies. The forcing data to simulate storm surge level using a hydrodynamic model (e.g.,) are wind fields and sea level pressure fields from an atmospheric reanalysis. Wind and sea level pressure conditions from a global reanalysis are used to obtain global storm surge databases. Regional simulations are driven by global or regional downscaled atmospheric conditions. Several examples of global and regional storm surge databases are described.

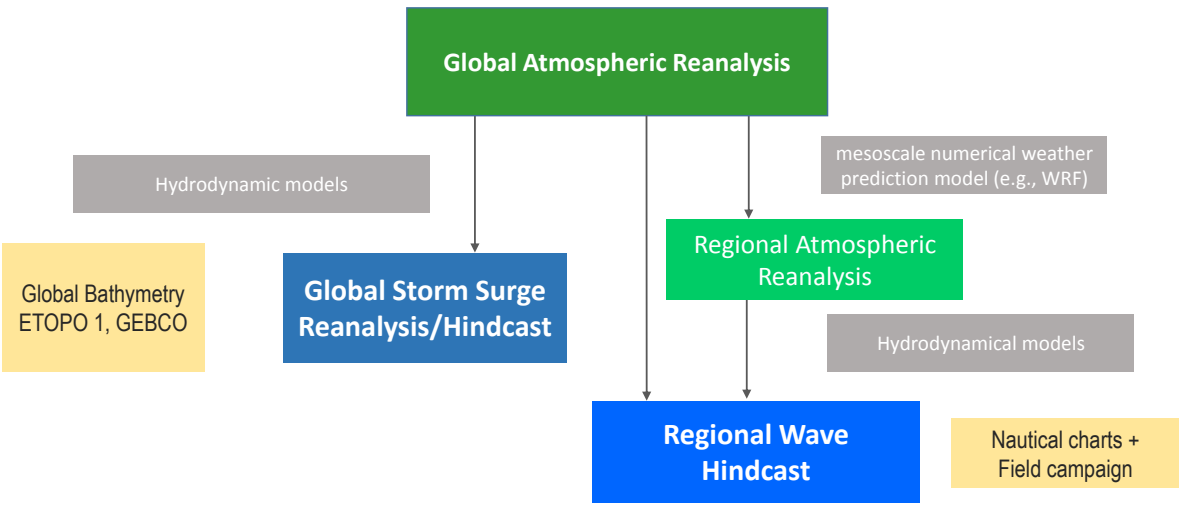


FIGURE 10 METHODOLOGY SCHEME TO GENERATE WAVE HINDCASTS AT DIFFERENT SPATIAL RESOLUTION.

GLOBAL SURGE HINDCAST

The surge database Dynamic Atmospheric Correction (DAC) was produced by CLS Space Oceanography Division using the MOG2D model from Legos and distributed by Aviso, with support from CNES (Carrère and Lyard, 2003). MOG2D (2 Dimensions Gravity Waves model) is a finite element, barotropic, non-linear, two-dimensional shallow water hydrodynamic model. The model is forced by pressure and wind fields from the European Centre for Medium-range Weather Forecasts (ECMWF) analysis, with a temporal resolution of 6 h and including shallow water areas and marginal seas. Barotropic sea level outputs span from September 1992 to present and are provided on a regular grid of 0.25◦ × 0.25◦ every 6 h. The operational DAC database is made of the high frequencies (i.e. less than 20 days) obtained from MOG2D barotropic model and the low frequencies of the inverse barometer (IB) assuming a static response of the ocean to the atmospheric forcing, and neglecting wind effects for low frequency (i.e. more than 20 days).

The first near-coast global reanalysis of storm surges (1979–2014) was developed using the new Global Tide and Surge Model (GTSM) forced with wind speed and atmospheric pressure from the ERA-Interim global atmospheric reanalysis (Muis et al., 2016). GTSM is based on the Delft3D Flexible Mesh software developed by Deltares. The application of unstructured grids (or 'flexible mesh') in hydrodynamic models make it possible to have a sufficient resolution in shallow coastal areas, while maintaining computational efficiency, and apply it on the global-scale. The cell size of the computational grid is dependent on the bathymetry and increases from 1/2° (~50 km) in deeper parts of the ocean towards 1/20° (~5 km) in shallow coastal areas (see Figure 11 with an example of the refinement of the computational grid in the Mediterranean Sea). The bathymetric data with a resolution of 1/60° are collected from the General Bathymetric Chart of Oceans and are interpolated onto the computational grid.

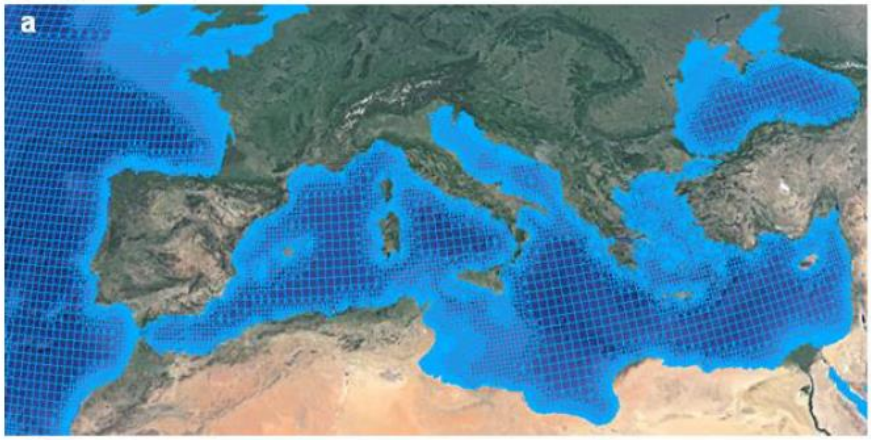


FIGURE 11 THE REFINEMENT OF THE GRID FROM THE DEEPER OCEAN TO MORE SHALLOW AREAS OF THE MEDITERRANEAN SEA OF THE COMPUTATIONAL GRID OF GTSM.

REGIONAL SURGE HINDCAST

Cid et al. (2014) developed two sets of 62-year (1948–2009) and 21-year (1989–2009) high-resolution hindcasts of the meteorological sea level component for Southern Europe using the Regional Ocean Model System (ROMS). The model domain encloses Southern Europe, including the Mediterranean Sea and the Atlantic coast, with a horizontal resolution of 1/8° (*14 km), see Figure 12. In order to study the effect of the atmospheric forcing resolution, ROMS was driven with two different regional atmospheric forcings: SeaWind I (30 km of horizontal resolution) and SeaWind II (15 km of horizontal resolution). Both are the result of a dynamical downscaling from global atmospheric reanalysis: NCEP global reanalysis and ERA-Interim global reanalysis, respectively (Menéndez et al., 2013). As a result, two surge data sets are obtained: GOS 1.1 (forced with SeaWind I) and GOS 2.1 (forced with SeaWind II).

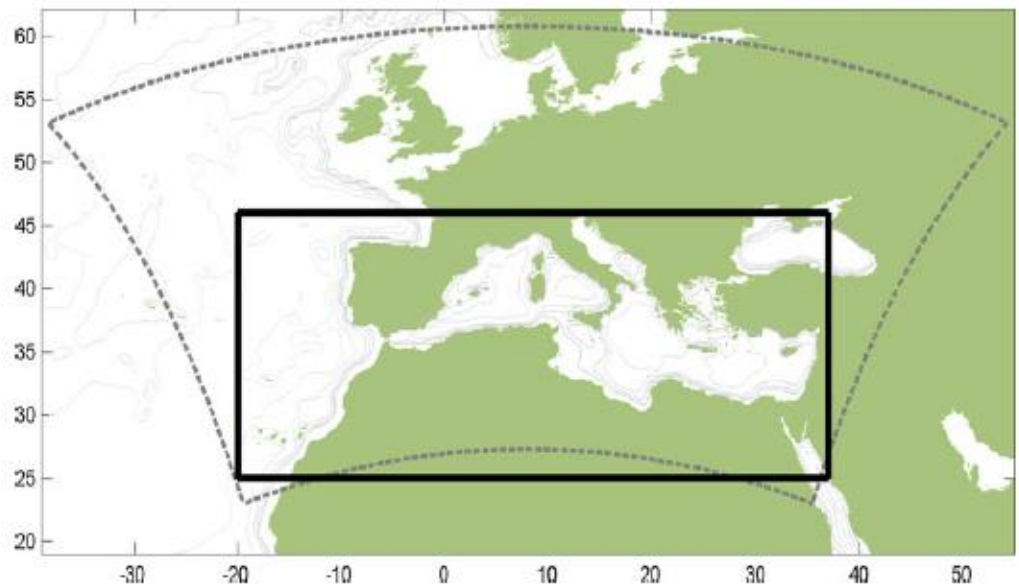


FIGURE 12 GRID DOMAIN OF STORM SURGE HINDCAST (BLACK LINE) AND ATMOSPHERIC DOWNSCALING (DASHED GRAY LINE) OF THE GOS DATABASE.

Flather et al. (1998) performed one of the first 40-year (1955–1994) hindcast simulations for North Sea storm surges. Wakelin et al. (2003) performed a tide-surge hindcast from 1955–2000 for the Northwest European Shelf. The North Sea storm surge hindcast 1958–2002 was developed using the TELEMAC2D model driven by hourly atmospheric wind and pressure fields at a spatial resolution of about 50 km (Weisse and Plüβ, 2006). These forcings were obtained from a dynamical downscaling of the National Centers for Environmental Prediction (NCEP) reanalysis using the regional atmosphere model SN-REMO. An unstructured mesh with triangular elements which vary between about 75 m near the coast and in the estuaries and 27 km in open sea regions was defined to take into account the complex coastline, islands, and bathymetric structures in the coastal zone and the mouths of the estuaries (see Figure 13).

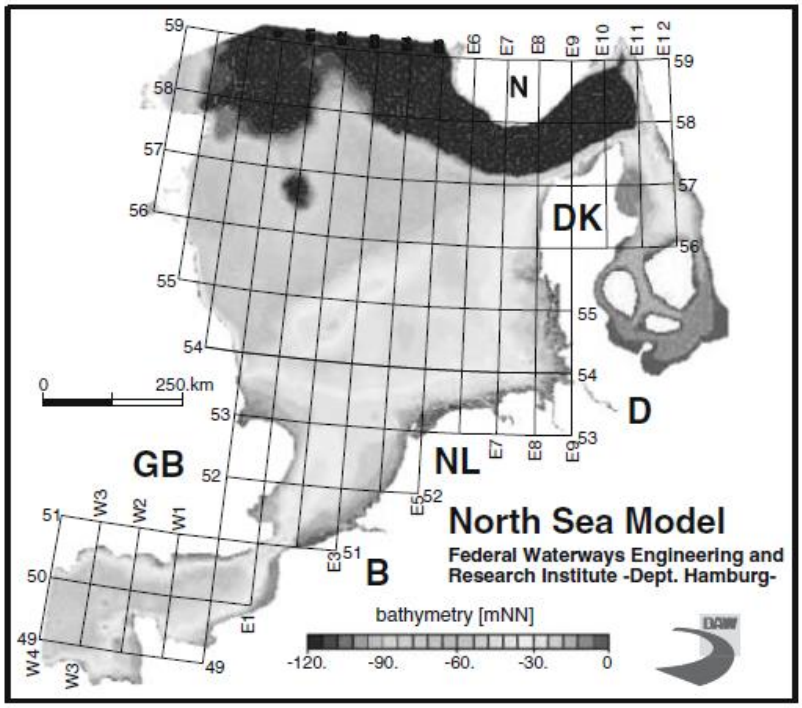


FIGURE 13 MODEL DOMAIN AND BATHYMETRY USED FOR THE SIMULATION OF THE NORTH SEA STORM SURGE HINDCAST.

Sebastião et al. (2008) generated a sea level hindcast for the Atlantic coast of Europe (including astronomic and meteorological effects) and Ratsimandresy et al. (2008) for the Mediterranean Sea. Both hindcasts were performed for the period 1958–2001 using a barotropic model (HAMSOM model) with a grid size of 10' in longitude and 15' in latitude. In both cases, the model was driven with wind and pressure fields with a resolution of 0.5°x0.5°. These atmospheric fields were created by means of dynamical downscaling from the global reanalysis NCEP, using the limited area model (LAM) REMO.

61-year time-series of storm surge component of the water levels around Australia were generated using a depth-averaged barotropic hydrodynamic model, the Danish Hydraulic Institute's Mike21 FM (flexible mesh) suite of modelling tools (Haigh et al., 2014). The model grid that was configured has a resolution of between 1/3rd and 1/5th of a degree (* 20 and 80 km) at the open tidal boundaries, increasing to 1/12th of a degree (* 10 km) along the entire coastline of mainland Australia, Tasmania and surrounding Islands. The grid was configured using the National Oceanic and Atmospheric Administration's medium resolution coastline. The bathymetric data, interpolated onto the model grid, was obtained from the Geoscience Australia 9 arc second (* 250 m) dataset. The model was forced with sea level pressure and 10 m wind fields, obtained from the NCEP/NCAR global reanalysis (Kalnay et al. 1996; Kistler et al. 2001), available every 6 h from 1948 with a horizontal resolution of 2.5°.

2.2 Statistical downscaling

The methods described in this section rely on the concept that regional climates are largely a function of the large-scale atmospheric state. In empirical downscaling the cross-scale relationship is expressed as a stochastic and/or deterministic function between a set of large-scale atmospheric variables (predictors) and local/regional climate variables (predictands). Predictor and predictand can be the same variables on different spatial scales, but more commonly are different (Giorgi et al., 2011). These models require historical data of the predictor (usually meteorological information) and predictand (in our case, sea surface dynamics). See Figure 14 with a scheme of the statistical downscaling approach. In the case of wave climate, we can distinguish different methodologies depending on the predictor definition: 1) atmospheric variables as sea level pressure fields and/or wind fields; 2) wave conditions at global/regional scale at deep water.

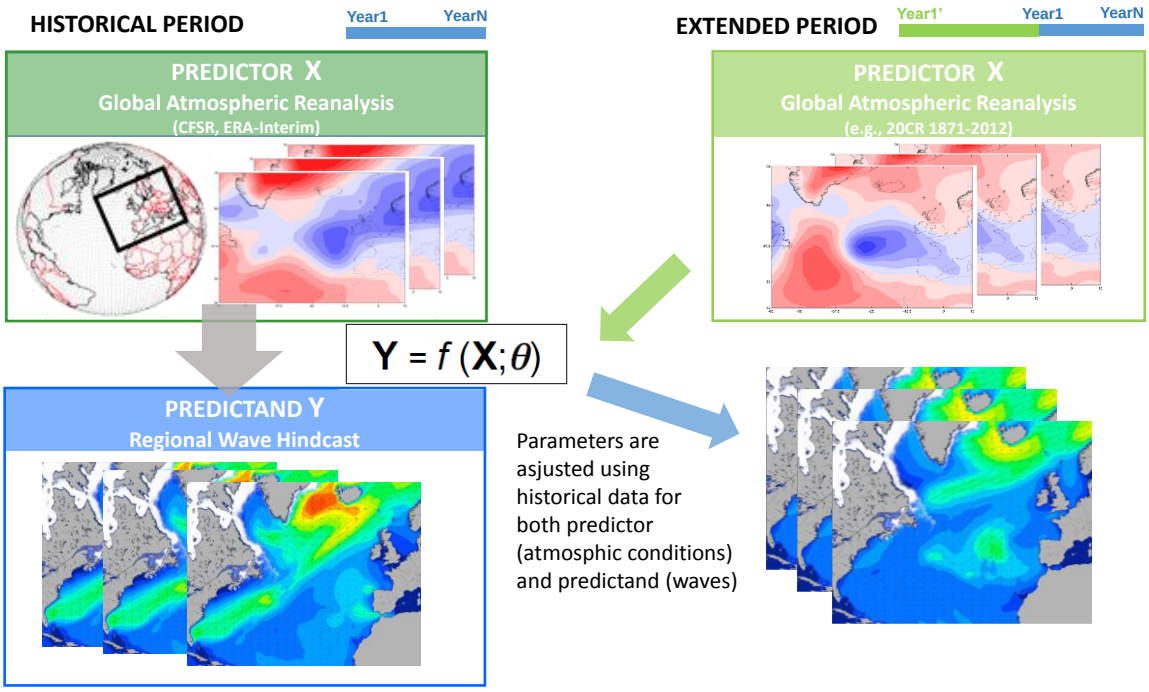


FIGURE 14 STATISTICAL DOWNSCALING APPROACH.

A diverse range of downscaling methods has been developed. Most of the approaches are however based on the following three techniques (Giorgi et al., 2011):

- Transfer functions, where a direct quantitative relationship is derived through, for example, regression;
- Weather typing schemes based on the more traditional synoptic climatology concept (including analogues and phase space partitioning) and which relate a particular atmospheric state to a set of local climate variables

- Weather generators, which are random number generators of realistic looking sequences of local climate variables, and may be conditioned upon the large-scale atmospheric state

Transfer functions are based on linear or non-linear (e.g. neural networks) regression models to infer the relationships between the large-scale predictors and the predictand. The more common transfer functions are derived from regression- like techniques or piecewise linear or non-linear interpolations. The simplest approach is to build multiple regression models with free atmosphere grid-cell values as predictors for surface variables (e.g., local temperatures). Other regression models have used fields of spatially distributed variables, principal components of geopotential height fields (e.g., Hewitson and Crane, 1992), Canonical Correlation Analysis (CCA) and a variant termed redundancy analysis (WASA, 1998) and Singular Value Decomposition (e.g., von Storch and Zwiers, 1999). An alternative to linear regression is piecewise linear or nonlinear interpolation, for example, the “kriging” tools from geostatistics. An alternative approach is based on Artificial Neural Networks (ANNs) that allow the fit of a more general class of statistical model.

Weather typing schemes are based on the local occurrences corresponding to a set of historical analogues (nearest neighbours) of the predictor fields (typically represented by large-scale circulation variables in a synoptic domain covering the area of interest). They are usually non-generative (not equation-based), since they consist of an algorithmic procedure. The analogue method is a popular and simple generic downscaling technique. Given an atmospheric state (as represented by a number of predictors defined on a particular geographical pattern) to be downscaled, this method finds the most similar historical atmospheric state (the “analogue" day, or nearest neighbour in terms of some metric, e.g. the Euclidean distance) in a pool of historical states provided by a reanalysis data set. Then, the downscaled values for the predictand are computed as the corresponding historical outcomes for the analogue date, thus producing spatially and physically consistent predictand values. Sometimes the predictors are pre-classified into a finite number of weather types, obtained according to their synoptic similarity (Casanueva, 2016).

Stochastic weather generators are statistical models used to simulate synthetic weather sequences, which are expected to be statistically similar to the observed counterparts (Wilks and Wilby, 1999). They are usually used with hydrological and environmental models for water resource and environmental management. More often, weather generators have been used as downscaling tools to produce high-resolution climate change projections by linking their parameters to climate model outputs. Compared to other statistical downscaling methods, such as regression-based approaches and weather typing schemes, the weather generator-based approach has the advantage of producing an ensemble of climate change projections for analysing risk-based environmental impacts.

Some examples of statistical approaches to downscale waves and storm surge are described below.

Transfer functions:

Kushnir et al. (1997) explored the nature and causes of the recent increase in North Atlantic wave heights by combining a numerical hindcast with a statistical analysis. The numerical hindcast incorporated a 10-yr history (1980–89) of North Atlantic, twice daily wind analyses to generate a monthly averaged significant wave height (SWH) history. The link between model-generated wintertime monthly SWH and monthly averaged sea level pressure (SLP) data was determined by means of a canonical correlation analysis (CCA). Using the CCA results, an extended statistical hindcast of monthly wave fields was generated from sea level pressure data and used to quantitatively estimate the systematic increase in wave heights since the 1960s.

Wang and Swail (2001) linked the seasonal extremes (90- and 99-percentiles) of significant wave height in the North Atlantic and the North Pacific, as simulated in a 40-yr global wave hindcast using the NCEP–NCAR reanalysis wind fields, with large scale atmospheric circulation (sea level pressure) patterns, as represented by the leading Principal Components of the relevant fields. The fitted statistical approach, called Redundancy Analysis, was used to extend the numerical hindcasts back to January 1899, providing a best guess of the historical variability of SWH extremes.

Wang et al. (2012) developed a multivariate regression model with lagged dependent variable is used to represent the relationship between the significant wave height (Hs) and the sea level pressure fields (SLP) at global scale. It is calibrated and validated using the ERA-Interim reanalysis of Hs and SLP for the period 1981–2010. Significant wave height is statistically reconstructed from the 20th century reanalysis (20CR) ensemble of SLP fields that spans over the past 140 years (1871–2010). For each wave grid point, a pool of 62 potential predictors are derived from the fields of squared SLP gradients and of SLP. In addition to the local SLP and squared SLP gradients, the 30 leading principal components (PCs) of the SLP fields and of the squared SLP gradient fields over an area that represents large scale patterns of atmospheric circulation (of the geostrophic wind energy) are included in order to model the swell components of waves generated remotely. A forward model-selection procedure is used to determine which and how many of the 62 potential predictors need to be retained in the regression model for a target wave grid point, using the F test with the equivalent sample size at the 5% significance level. This model was also used to project 6-hourly significant wave height along the XXI century for different climate change scenarios (RCP4.5 and RPC8.5) in Wang et al. (2014).

An improvement of the regression model proposed by Wang et al. (2012) was developed by Casas-Prat et al. (2014) for modelling 3-hourly Hs in the near shore areas along the Catalan coast. The method uses the PCs derived from the squared SLP gradient vectors (including magnitudes and directions). By retaining the geostrophic wind direction information and separating between its positive and negative phase, this approach enables the detection of swell wave trains affecting each wave grid location. The time lag between the wave generation area and the propagated swell at the point of interest is also considered. Based on the directional/frequency dispersion of waves, each swell train is finally weighted as a function of the considered frequency bin and the deviation of the swell wave train propagation from the forcing wind direction at the origin.

In the context of climate change, other multivariate regression models has been proposed to project significant wave height in the future under different climate change

scenarios at seasonal at seasonal to interannual time scale using sea level pressure fields or wind fields (Martínez-Asensio et al., 2016). Mori et al. (2013) projected wave height using an empirical formula as a function of sea surface winds.

The global surge database DAC developed by AVISO fulfilled the lack of data in terms of spatial coverage, but not regarding time extent, since it only includes the last two decades (1992–2014). A multivariate linear regression model is fitted between daily mean ERA-interim sea level pressure fields and daily maximum surge levels from the global database DAC (Cid et al., 2017). The statistical model is used to reconstruct daily surges using mean sea level pressure fields from 20CR providing a daily database of maximum surge levels which correspond to an extension of the DAC database, from 1871 to 2010. The statistical method comprises a multivariate regression model fitted between daily maximum surge level (predictand) and the principal components (PCs) of the mean daily SLP and gradients (predictor). The first step in the methodology consists in performing a principal component analysis (PCA) of the predictor to reduce the dimensionality of the problem while preserving the maximum variance of the data sample. The transformed components of the original data over the new vectors are the principal components (PCs). The multivariate regression model between the predictor PCs that explains the 95% of the variance and the surge levels is fitted in a forward procedure until a more complex model does not produce a significant improvement (at the 5% level of significance).

A technique based on artificial neural networks (ANN) of the type radial basis function (RBF) was developed to estimate daily significant wave heights at a coastal location based on the wave heights sensed by a satellite along its tracks (Kalra et al., 2005). The training data are the significant wave height in several locations along the satellite data and the significant wave height recorded by a coastal buoy. The selected method of providing input information, namely significant wave heights over a sufficiently large number of points near a selected track, was necessary in order to consider the effect of all deep water stations in the occurrence of waves at the target coastal station.

Browne et al. (2007) tested ANNs for modeling the near-shore wave transformation: bringing global ocean wave model output to near-shore locations, and demonstrating a potentially useful tool for emulating expensive surf reporter observations. A comprehensive evaluation of empirical methods is attempted by considering a total of 17 onshore locations across 5 geographical regions distributed across the continent of Australia, for a period of 8 months. The values of the significant wave height, wave period and wave direction of the principal swell component, sea component and secondary swell component, and the wind velocity and wind direction.

Weather typing schemes

A statistical downscaling method was developed by Camus et al. (2014) based on weather types (WTs) to downscale multivariate wave climate. The predictor defined by the daily sea level pressure (SLP) fields from a reanalysis atmospheric database over the local wave (predictand) generation area is classified into a reduced number of WTs (100 in that work). PCA is applied to this daily predictor to reduce the data dimensionality and simplify the application of the classification technique. Weather types are obtained using KMA technique, with a post-organization onto a bidimensional lattice by a similarity criterion.

First, the statistical relationship is established by identifying hourly sea state parameters at each location of interest in each daily predictor field within the corresponding cluster (WT). Then, the empirical probability distribution of each sea state parameter (e.g., significant wave height) associated with each WT is calculated. Finally, the complete distribution of this variable for a particular time period can be estimated as the probability sum of each WT during that period multiplied by the corresponding empirical distribution. As a result, different statistics (e.g., mean, 95th percentile) can be derived from the estimated distribution. Daily SLP and daily squared SLP gradients (SLPG) are taken as atmospheric variables to define the wave predictor. The predictor is defined as the leading principal components (PCs), which explain 95% of the entire predictor variance of the m-daily mean SLP, with m=3 days for the North Atlantic. These values were obtained on the same day and the previous m-1 days as the SLP average throughout the historical time in order to model the swell component. The statistical downscaling model is able to produce long historical reconstructions of multivariate wave climate over different time scales from the reanalysis long-term period. For example, SLP forcing from 20CR reanalysis was used to reconstruct local waves through the XX century at several locations on the Atlantic coast of Europe.

Weather generators:

Rueda et al. (2016a) proposed a classification of weather patterns to statistically downscaledaily significant wave height maxima to a local area of interest. A stationary extreme model (e.g., GEV) is fitted on the predictand (daily maximum significant wave height) associated to each weather type (WT). The associated return periods are obtained performing the convolution of the extreme distribution functions of the WTs, taking into account the dependence of daily maximum by an extremal index (defined as the mean WT duration), the probability of the each WT and the number of block maxima (at annual or monthly scale). Nonstationarity (seasonality, interannual variability and climate change) is introduced in the model through time-dependent occurrence probabilities of the WTs. A reconstruction of monthly maxima estimates for the twentieth century has been performed based on WTs probabilities obtained with SLP fields from 20CR atmospheric reanalysis. Rueda et al. (2016b) extend the proposed a method to define a climate emulator to predict compounds extreme events (wave and storm surge) based on weather patterns. For each weather type, marginals of the significant wave height, mean period, and storm surge are fit to a GEV distribution and a Gaussian copula is used for modelling the interdependence between variables.

2.3 Hybrid downscaling

Hybrid methodologies have been developed mainly to generate wave information at high spatial resolution nearshore (50-250 m is typically required for design purposes in coastal engineering, see Figure 15). Wave reanalysis databases solve the shortcomings of instrumental data related to inhomogeneities and lack of spatial and temporal coverage.

However, waves are poorly described at shallow water areas because the spatial resolution is not sufficiently detailed and wave transformations due to the interaction with the bathymetry are not usually modelled. The modelling of the transformation processes are simulated using numerical wave propagation models.

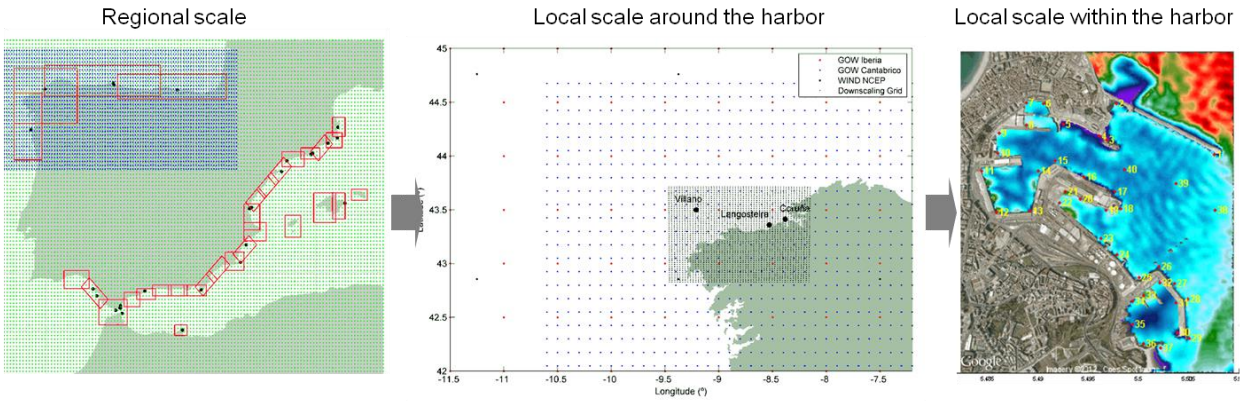


FIGURE 15 "DOWNSCALING" TO OBTAIN THE LOCAL DYNAMICS AROUND AND INSIDE THE PORTS.

The most common hybrid methodologies consist of developing a transfer function for the transformation of offshore wave conditions to nearshore locations through the numerical propagation of a number of sea state conditions which characterize deep water wave climate (dynamical downscaling), see for instance Groeneweg et al. (2007) and Stansby et al. (2007). The traditional approach is to develop a 'look-up table' which involves running the model for a subset of events defined over a regular grid with a coarse resolution to limit the number of simulations. Two approaches with a different degree of complexity can be applied to predict the results for additional events: selecting the result of the most similar design point as representative of the new event, or using linear interpolation techniques.

The representative cases are defined by means of several combinations of offshore wave and/or wind conditions at a specific location, without considering the spatial variability of these forcings. In order to correctly define the transfer function, a large number of sea states need to be simulated numerically, especially if the number of offshore wave parameters increases and therefore, the number of parameter combinations (Chini et al., 2010).

Breivik et al. (2009) defined a linear downscaling based on 1-year hourly dynamical simulations, nested to the outputs of a third-generation wave model and forced by high resolution winds. However, the coastal wave height is estimated by means of a simpler linear relation with the height at a coarse resolution open-ocean reanalysis grid, including the wave direction dependency via the definition of four regression models corresponding to four different directional sectors.

In addition to these hybrid methods, more sophisticated methodologies have been developed to obtain high resolution nearshore wave statistics. Galiskova and Weisse (2006) proposed three different statistical models based on linear regression, canonical correlation analysis and analogs to define a relation between instantaneous medium-scale wave fields from a hindcast database and higher resolution wave data in shallow water

obtained dynamically. The empirical relations established are used to reconstruct certain percentiles of the significant wave height.

Another statistical–dynamical approach, developed by Herman et al. (2009), uses a combination of a numerical model, principal component analysis and a neural-network method. This methodology reconstructs the spatial wave fields in shallow water as a function of the wave conditions, wind conditions and the sea level at a certain location because the forcings are highly uniform in the study area. These two methodologies require propagating several years of dynamical downscaling to generate the statistical model and its validation (Galiskova and Weisse, 2006; Herman et al., 2009).

Camus et al. (2011b) proposes a hybrid methodology which combines numerical models (dynamical downscaling) and mathematical tools (statistical downscaling). The methodology consists of the selection of a small number of representative wave conditions at deep water using the Maximum Dissimilarity Algorithm (MDA, see the analysis of selection algorithms of multivariate sea states presented in Camus et al., 2011a), the propagation of the selected cases using any state-of-the-art wave propagation model and the reconstruction of the wave time series at shallow water by means of the interpolation algorithm based on the radial basis functions (RBFs). The computational time required is significantly less than the other hybrid methodologies proposed because MDA covers the whole diversity of the offshore conditions with a reduced number of cases. Moreover, the RBFs allow establishing the statistical relation as a function of more offshore parameters.

An extension of the hybrid method (Camus et al., 2013) is developed to generate hourly coastal wave time series trying to emulate the characteristics of the coastal wave reanalysis databases obtained by means of dynamical downscaling but reducing the computational time. This improved version of the methodology takes into account the spatial variability of the wave boundaries of the propagation domain and the local wind wave generation, using the simultaneous wind fields, in a similar way as if the coastal wave databases were generated by means of dynamical downscaling. Therefore, the new methodology is adapted to high dimensional wave and wind data in deep water. Although the MDA and RBF methods are able to deal with highly dimensional data, a previous reduction of the dimension is applied using PCA in order to simplify the selection and reconstruction processes.

A coastal wave reanalysis database (downscaled ocean waves, DOW) is generated using the extended hybrid methodology (see Figure 16). The GOW database at a regional scale is used as wave forcing to generate the nearshore wave reanalysis. The SeaWind database, generated with a dynamical downscaling of NCEP/NCAR wind reanalysis at a spatial scale of 30 km (Menéndez et al.,2013), is used as wind forcing. Both reanalysis databases have been calibrated previously. Propagation domains have been established covering the entire Spanish nearshore region with a resolution of 0.01°x0.008° (low-resolution meshes), with several nested meshes reaching a resolution of 50 m around the most important ports (mid-resolution and high resolution meshes). The proposed hybrid methodology has been applied in each general grid, using the 500 cases selected by the MDA as boundary conditions for the SWAN Model. Whilst the selection is undertaken using the summary parameters, the numerical propagation are forced using the full wave spectrum at the computational boundaries, providing a more realistic wave simulation

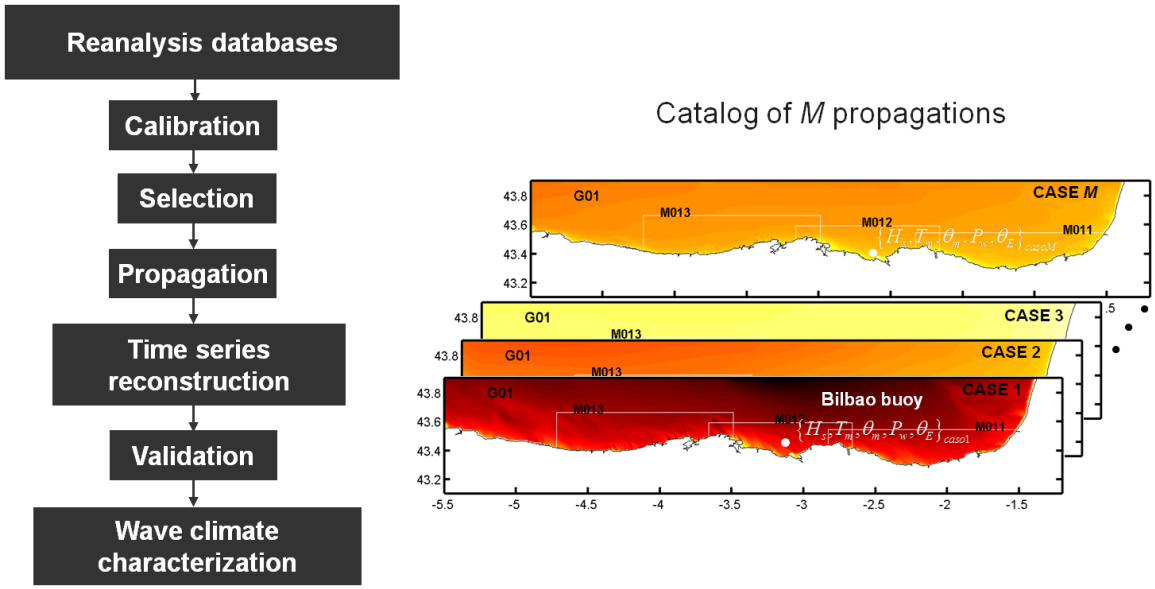


FIGURE 16 HYBRID METHODOLOGY TO TRANSFER OFFSHORE WAVE CLIMATE TO NEARSHORE AREAS (CAMUS ET AL., 2013).

3. Discussion about downscaling approaches

Different downscaling strategies to generate long-term historical databases of waves and storm surge at a resolution suitable for regional studies are reviewed. These methodologies can be classified in three categories: dynamical, statistical and hybrid downscaling.

The dynamical downscaling approach performs every hourly simulation using nested computational grids with increasing resolution or using a flexible mesh with higher resolution in coastal areas (e.g., global storm surge reanalysis). Wave climate in many coastal areas are due to a combination of local sea waves and swells that travel long distances which requires to be downscaled from a global simulation. This approach gives the best results in terms of accuracy, temporal resolution and spatial coverage, however, it is very demanding computationally.

Another important issue regarding waves is the multidimensionality of the parameters that define a sea state. Many ocean and coastal engineering applications and coastal impact assessments require not only the significant wave height, but also the wave period (peak, mean, energetic) and wave direction (e.g., particularly critical for calculating littoral drift and associated estimates of sand budgets to determine coastal erosion sediment transport, Hemer et al., 2010b). Therefore, the dynamical modelling provides all the sea state parameters while statistical downscaling approaches presents the limitation of the reconstruction of only one parameter using regression models or daily parameters using a weather type approach.

Besides, statistical downscaling approach requires historical information of the predictor (usually atmospheric fields but also waves at higher resolution) and the predictand (regional or local sea state parameters) to establish the relationship. The main purpose of this approach is to provide an extension of the historical wave data in a different time period. Long observation time series of the predictor and predictand are necessary to take into account as much as possible the natural variability, especially for extreme events. The predictor selection is critical and should guarantee the physical explanation of the relation between the large-scale predictor and the local predictand. The screening of the variables, its geographical domain and temporal lag is a very time-consuming but once the optimal predictor is established, the main advantage of the statistical approach is that it is computationally inexpensive. Therefore, it is suitable to get long-term simulations, or to develop multiple realizations from different forcing conditions (i.e., 20CR ensemble).

The spatial resolution and spatial representativeness of an statistical downscaling method depend on the underlying observational/hindcast data set used as a reference while applying a dynamical downscaling a sequence of nested computational grids are required to reach a sufficient spatial resolution for the case study. Moreover, spectral data is necessary to define wave boundary conditions in order not to assume any hypothesis about the spectral shape.

Extreme events is another delicate issue. The quality of wind fields are the key factor to reproduce extreme waves or storm surge using a dynamical downscaling approach. Statistical downscaling methods based on linear regression methods has some limitations about the skill of extreme estimations (although a lagged dependent variable was introduced to improve it, Wang et al., 2014) while weather-typing methods only are able to reproduce high percentiles (Camus et al., 2014).

Statistical downscaling methods are developed mainly in the climate change context because present some advantages over dynamical downscaling: the biases in climate-model-simulated climate and variability of the atmospheric circulation (or predictors in general) can be effectively diminished by using standardized predictor quantities in statistical downscaling models (Wang et al. 2010), they can used as predictors the global atmospheric variables simulated with higher accuracy.

Regarding hybrid downscaling methodologies, the huge number of sea states to propagate leads to different strategies which aim to reduce the computational effort. The more common methodologies consist of replacing all available data with a small number of representative sea states, which are later propagated to shallow water areas. A transfer function is defined allowing the propagation of all the sea states of the long-term series of wave parameters in deep waters by means of an interpolation algorithm (Groeneweg et al., 2007; Stansby et al., 2007). The transfer function of some hybrid methods usually requires propagating (dynamical downscaling) a considerable number of sea states in order to represent the climate variability for deep water (Chini et al., 2010) or several years of dynamical downscaling to generate the statistical model and its validation (Galiskova and Weisse, 2006; Herman et al., 2009). On the other hand, these more sophisticated methods are able to reproduce spatial wave statistical parameters. Data mining algorithms that synthesize huge amount of multidimensional information have improved the

representativeness of the selected cases and have improved the ability of the interpolation scheme (Camus et al., 2011).

4. Total water level

Coastal flooding often occurs during extreme water-level events that result from simultaneous, combined contributions, such as large waves, storm surge, high tides, and mean sea-level anomalies. Flooding results from the complex interaction of extreme water levels, topography, and the built environment (coastal defense structures, and drainage systems). The maximum potential flood hazard is usually represented by the proxy named total water level (TWL), defined as the sum of the astronomical tide, storm surge, and wave runup, referenced to mean sea level (see Figure 17). Runup is defined as the set of discrete water level elevation maxima due to wave transformations in the surf zone, measured on the foreshore, with respect to still water level. This includes wave set-up, the super-elevation of the mean water level, is driven by the cross-shore gradient in radiation stress that results from wave breaking, and swash, which corresponds to the vertical fluctuation of the water line above the still water level induced by individual waves.

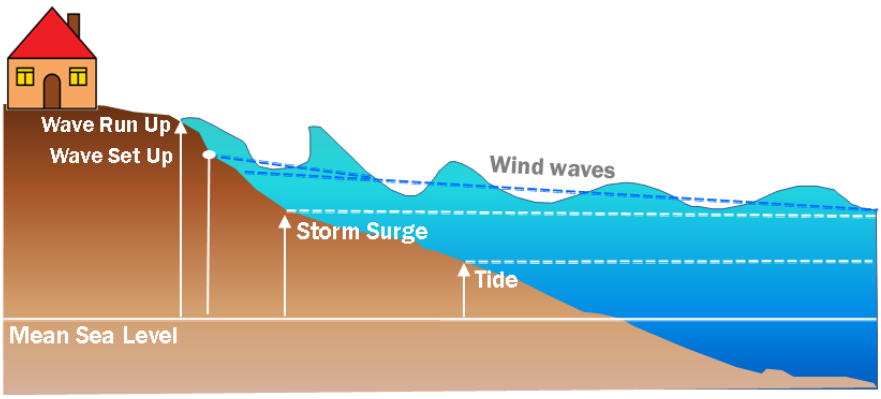


FIGURE 17. THE WATER-LEVEL COMPONENTS THAT CONTRIBUTE TO COASTAL FLOODING.

Therefore, to characterize TWL is necessary coincident data for waves, tides, and storm surge composed of long continuous hourly time series at an adequate spatial resolution to the scale of the study.

Some studies about the flooding impact at a global scale have only taken into account sea level variations due to tides and atmospheric surges (Nicholls, et al. 2014, Muis et al., 2016). Recent ones have introduced the wave component using an empirical formulation (Stockdon et al., 2006) with a different complexity degree (i.e., only setup component as in Vousdoukas et al. 2018, Rueda et al., 2017 and Vitousek et al. 2016, setup and swash in Melet et al. 2018). Well-validated global tide, wave, and storm surge reanalysis models are used to provide a time series of total water level (TWL) in all these studies, as for example, time series of storm surge from the DAC database or the one obtained from GTSM model,

or time series of sea state parameters from GOW or ERA-Interim databases. Therefore, validated hindcast/reanalysis products offer long, spatially-homogeneous time series of water-levels and wave parameters for a uniform coastal impact assessment. Time series of TWL from high-resolution coastal wave and storm surge databases have also been used to define the forcings of a regional scale using process-based flood model.

Nonlinear interactions between tide, surge, and wave-driven water levels are not accounted in any of these studies. These processes may be important in some coastal regions, especially with shallow bathymetry but due to the computational effort required they are only considered in very specific local studies.

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